The use of satellite-derived data and neural-network analysis to examine variation in maize yield under changing climate

By

ADISA Omolola Mayowa

Submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

(Geoinformatics)

In the Faculty of Natural & Agricultural Sciences

University of Pretoria

Pretoria

June 2019

The use of satellite-derived data and neural-network analysis to examine variation in maize yield under changing climate

Student : Adisa Omolola Mayowa (13387562)

Supervisor : Dr Daniel Darkey

SIGNATURE: ……………………………

DATE: …………………………………….

Co-supervisor 1 : Dr Joel Ondego Botai

SIGNATURE: ……………………………

DATE: …………………………………….

Co-supervisor 2 : Prof Abubeker Hassen

SIGNATURE: ……………………………

DATE: …………………………………….

Co-supervisor 3 : Dr Eyob Tesfamariam

SIGNATURE: ……………………………

DATE: …………………………………….

Department : Geography, Geoinformatics and Meteorology.

Degree : PhD Geoinformatics

Declaration

I, **Adisa Omolola Mayowa** declare that the thesis, which I hereby submit for the degree of ***PhD Geoinformatics*** at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

SIGNATURE: ……………………………

DATE: …………………………………….

Disclaimer and thesis structure

This thesis adapts the publication style of writing. The seven chaptered study basically has four objectives and it is intended that all objectives as well as the literature review would be published. Consequently, three articles have been published in peer-reviewed journals. The three articles cover objective 1 (chapter 3), objective 2 (chapter 4) and objective 4 (chapter 6). The third objective is achieved in chapter 5. Chapter 5 has been peer-reviewed and accepted for publication with *Journal of Agricultural Meteorology*. The chapter 2 is the literature review and it is equally under review for publication in an international journal. Chapter 1, the general introduction to the study and chapter 7, provides the summary, conclusion and recommendation of the thesis.

To this end, the content and style of presentation may vary or overlap between chapters in order to meet with the publication specific journal requirements. Figures in some chapters appear within the text, and in other chapters they have been added at the end of the chapters.

Some of the publications have more than three authors, but this does not mean that work was done proportionately. Work in these publications is solely my effort and originally initiated by me as the principal investigator.

Table of Contents

Dedication

This research is dedicated to the giver of life and the lover of my soul, the Lord Jesus; for granting the grace that saw me through this study.

Acknowledgements

This study would not have been successful without significant support and assistance from a number of angels in human flesh. I would like to thank my supervisor; Dr Daniel Darkey and Co-supervisors; Dr Joel Botai, Prof Abubeker Hassen and Dr Eyob Tesfamariam for their mentorship and guidiance during this study. Thank you for the 2-year bursary from AnimalChange project (European Commission's Seventh Framework Research Programme). The opportunities I had and utilised were far reaching.

I would like to express my appreciation to my parents; Pastor (Prof) Alex Adisa and Pastor (Mrs) Olubola Adisa, for giving me a solid foundation to build on. To my brother and sisters, my uncles and aunties for their prayers and words of encouragement during this study.

I am eternally grateful to Dr Olalekan Taiwo of the department of Geography, University of Ibadan, for instilling the academic rigor I had under him during my Masters programme. It extremely paid off giving me an edge for endurance, perseverance and thoroughness in academic/research pursuit in South Africa. Thank you for being the channel to which this study was possible in South Africa through one of the numerous opportunities my husband and I had under your mentorship.

I want to appreciate all friends and colleagues of the department of Geography, Geoinformatics and Meteorology, University of Pretoria for providing such a unique environment for this study. Your inputs during the writing of the articles are indeed appreciated.

Many thanks to the Pastorate and the entire members of the Redeemed Christian Church of God (RCCG) Mount Zion Parish, Pretoria for providing the spiritual support that saw me through this study.

In all, I deeply appreciate my crown and husband of inestimable value; Dr Abiodun Adeola '*Ifemi*'. You are such a sent from God. Thanks for all the love and care that have kept me going even through the hard time of this research. To wonderful heritages from God; my daughter; Toluwalase Olabamigbe and son; Toluwalope Josiah for their immeasurable love, encouragement, understanding, tolerance and patience throughout this bumping journey.

And above all to the Lord, the Almighty, the Alpha and Omega, my strength and wisdom. Thank you for starting and finishing this study with me.

Abstract

Climate change and variability is foreseen to have direct and indirect effects on the existing agricultural production systems potentially threatening local, regional and/or global food security depending on the spatial scale of the change. The trend and level of impact caused by climate change and/or variability is region dependent and adaptive capacity. Climate change is projected to have more adverse impact in high vulnerability areas of sub-Saharan Africa.

This study aimed to examine the variation in maize yield and develop a framework for predicting maize yield in response to climate change. To achieve this aim, this study has analyzed the impact of agro-climatic parameters on maize production across the major four maize producing provinces of South Africa. This study went further to investigate changes in the satellite derived phenological parameters and its relationship with maize production. In addition, the influence of drought (a derivative of climate change) on maize production was investigated. The study concluded by integrating all datasets used in each objective to develop an empirical predicting model using artificial neural network. Previous studies have quantified the impact of climatic variables on maize and at a small geographic area. Attempts to predict maize yield have been minimal and the use of artificial intelligence such as the artificial neural network has not been conducted. In this study, alternative sources of climatic and environmental data have been employed using remotely sensed data which offers possibilities of collecting continuous data over a large area (including remote areas) through the use of satellite.

The analysis of agro-climatic variables (precipitation, potential evapotranspiration, minimum and maximum temperatures) spanning a period of 1986–2015, over the North West, Free State, Mpumalanga and KwaZulu-Natal (KZN) provinces, indicated that there is a negative trend in precipitation for North West and Free State provinces and positive trend in maximum temperature for all the provinces over the study period. Further more, the result showed that one or more different agro-climatic variables has more influence on maize across the provinces.

Analysis of the phenological parameters of maize indicated that climate change and climate variability affect plant phenology largely during the vegetative and reproductive stages. NDVI values exhibited a decreasing trend across the maize producing provinces of South Africa. The results further demonstrate that the influences of climate variables on phenological parameters exhibit a strong space-time and common covariate dependence. Agro-climatic variables can

predict about 46% of the variability of phenology indicators and about 63% of the variability of yield indicators for the entire study area.

The study also illustrated the spatial patterns of drought depicting drought severity, frequency, and intensity which has the potential to influence crop yield. The study found that maize yield is most sensitive to 3-month timescale coinciding with maize growing season ($r = 0.59$; $p < 0.05$) affecting maize yield by up to 35% across the study area.

In ensuring and fulfilling one of the seventeen sustainable development goals; to *eradicate extreme poverty and hunger,* the development of a system capable of monitoring and predicting crop yield becomes imperative. Machine learning tools such as the artificial neural network becomes handy and useful to provide a platform that is data intensive and robust to meet the requirements for an effective monitoring and predictive system for crop; particularly maize. The accuracy of the comparison between the actual and predicted maize yield is averaged at about 92% across the study area. The empirical model developed in this study can also be adopted to other grain crops such as Sorghum, wheat, soya beans etc.

Abbreviations

ANN: Artificial Neural Network

CDM: Consecutive Drought Months

CI: Confidence Interval

DD: Drought Duration

DMI: Drought Monitoring Indicators

DS: Drought Severity

EIU: Economist Intelligence Unit

EOS: End of Season

EVI: Enhanced Vegetation Index

FAO: Food and Agricultural Organization

FS: Free State

GDP: Gross Domestic Production

GHG: Greenhouse Gases

GIS: Geographic Information Systems

GPS: Global Positioning System

IPCC: Intergovernmental Panel on Climate Change

KZN: KwaZulu-Natal

LOS: Length of Season

MODIS: Moderate Resolution Imaging Spectroradiometer

MP: Mpumalanga

NDVI: Normalised Difference Vegetation Index

NIR: Near-Infrared

NW: North West

PCA: Principal Component Analysis

PET: Potential Evapotranspiration

PLS-PM: Partial Least Square Path Modeling

POP: Position of Peak Value

POT: Position of Trough Value

PRE: Precipitation

RS: Remote Sensing

SA: South Africa

SADC: South African Development Community

SOS: Start of Season

SPEI: Standardized Precipitation Evapotranspiration Index

SPI: Standardized Precipitation Index

TMN: Minimum Temperature

TMX: Maximum Temperature

USGS: United States Geological Survey

List of figures

List of tables

Chapter 1

GENERAL INTRODUCTION

1.0. Introduction

This chapter gives a brief introduction to the study. It starts by giving background of the subject matter 'maize' in relation of its relationship with climate and other derivatives such as changes in phenology and drought. This session went further to give a snap shot of maize production, globally, regionally, nationally and locally in South Africa. In addition, this chapter gives a preview to the major themes of the study. The major themes of this study aside maize are; climate, phenology (remote sensing), drought and prediction. These themes are further discussed in detail within each of the corresponding chapters. This thesis adopts the publication style of thesis writing. Each objectives of the research are presented in the format of an academic paper/publication. Hence, each objective forms a chapter and their methodologies were defined and explained therein. Additionally, this chapter, presents the research motivation, the research questions, aim and objectives of the study.

1.1. Maize

Maize called binomially as *Zea mays L*. is a member of the grass family called *Poaceae*. The *Poaceae* is a family of monocotyledonous flowering plants collectively known as grass. They include cereal grasses such as Oats, Rice, Sorghum, Wheat and maize (CFIA, 2014). Maize is a leafy stalk called an angiosperm, which implies that its seeds are enclosed inside shell (CFIA, 2014). Maize is believed to have originated in Mexico in prehistoric times and serves as a staple food in Central and South America and parts of Africa and grown mostly for use as animal feed in Europe and the rest of North America (Verheye 2010).

Maize can be grown on a great variety of soil types, however, the most suitable soil type for cultivating maize is a soil with a good effective depth, good texture and structure, good internal drainage, an optimal moisture regime, sufficient and balanced quantities of plant nutrients and chemical properties. Climatically, temperature ranges from 19 to 25 °C is ideal for the maize flowering. Temperature values of above 32 °C is harmful to the yield. A frost-free period between 120 to 140 days is required to prevent loss of yield. Aside practice of intensive irrigation, an annual rainfall above 500 mm is required for maintaining adequate moisture. Water deficiency is usually the most yield-limiting factor where efficient maize cultivation practices are applied. A yield of 3152 kg ha-1 requires between 350 and 450 mm of rain per annum (Du Jean 2003).

Maize either white or yellow is a staple food in many countries including Central and South America and Africa and Asia. Maize is an important part of American foods as corn starch. It is utilized in the form of grain, meal and green mealies. Processed maize is consumed as a snack (popcorn) and cereal. Industrially, maize is used by Millers for livestock feed. It is fed to livestock as hay or silage. Maize in South Africa is the most important grain crop, it is the staple food for most people in the country and the main grain for feed. However, it is expected that the ratio between animal feed and human consumption will change since the patterns in the demand by animal feed is changing and the growth in the middle-class population. According to Rosegrant et al., (2008), demand for maize in the developing world is predicted to double by 2050, also by 2025 maize is predicted to ascend the position of the crop with the greatest production globally and in the developing countries of the world. Majority of the maize produced in South Africa is locally consumed, this add great importance to the domestic market in the industry. About 7 million tons is required for local consumption per year. Although maize is produced throughout the country, but Free State, Mpumalanga and North West produces over four-fifth of the total production making these Provinces the largest producers of maize in South Africa. Maize in the country is commonly rain-fed grown on dry land predominantly, planted between mid-October and mid-December, with less than 10% produced under irrigation. Agronomists has been battling with the issue of how best to increase maize yields over the years (Cai et al., 2006). Although according to Wang 2000 and Xiao et al 2008 a combination of high-yield varieties with the best crop management practices would increase grain production. However, climate change as have its fair effect on maize yield.

1.1.1. Maize and climate change

Constant emissions of anthropogenic greenhouse gases have been agreed by scientists to continue to hasten climate change and its impact on agriculture globally (Den Elzen et al., 2010; IPCC 2007). For several decades now, existence of global warming trends has been documented at most locations around the world, which is projected to increase in the future (Tao et al., 2006). And of recent climate change has topped the table of scientific problems and all communities throughout the world are equally concerned about it (Alexandrov et al., 2000). It is predicted by

Intergovernmental Panel on Climate Change (IPCC) 2000 that there is likely to be a warming of about 0.2^{o}C in the next two decades. And as reported in the fourth report by the IPCC the average global temperature increased by about 0.74±0.18 ∘C annually during from 1906-2005 (IPCC 2007). Furthermore, lots of studies highlighting these changes and variability have been carried out at different locations all over the world (Shobha et al., 2016; Guoyoug et al., 2017).

The sector most vulnerable to climate changes, variability and extremes is the food systems and agricultural sector. Noticeable by the effect climate change has on crop production and the undoubtedly fact that a nation's food security is highly dependent on climate variability (Liu et al., 2010). Since these two systems are socio-economical important it is of paramount importance to assess the future effect of climate change on crop productivity (Bindi et al., 2011). Generally, climate change poses a negative threat on agricultural production particularly in the dry and hot areas (Gregory et al., 2005), except for some areas located above 55^{o}latitude where it will have positive effects (Ewert et al., 2005). Of recent, scientific studies (Ummenhofer et al., 2014; Nadiezhda et al., 2017) has tended towards climate variability and impact of climate change on crop production and agriculture.

Changing climate, that is elevated atmospheric CO_2 concentrations, various rainfall patterns, and extreme temperature for example has been included among the important factors affecting crop yield. Chiotti and Johnston in 1995 speculated that climate change could have substantial impacts on agriculture in future and the possible impacts of this change on crops have been of utmost concern which many researchers (Tao et al., 2006; Yang et al., 2008) have evaluated extensively. In attempt to quantify the local impact of climate change, researchers are faced with challenges like the diversity of agricultural systems, the possible effect of global changes, and variations in the amount of CO_2 available for photosynthesis. Also, climatic factors such as pressure, moisture, precipitation and temperature affect plant development, either in isolation or by interacting with other factors (Curforth et al., 2007). Furthermore, climate change has an adverse influence on the quality of the natural environment, the landscape, land-use, land suitable for food, crop yield and growing periods (Daccache et al., 2015).

A better understanding of the relationship between crop yield and climate assist in increasing the flexibility of agricultural production systems to climate change. In this vein, several studies have been conducted, exploring how crop yield respond to climate conditions, with great emphasis on extreme climate (Lesk et al., 2016; Lobell et al., 2014), inter-annual and decadal climate variability (Lobell et al., 2011a; Schlenker et al., 2009), climate co-variability (Leng et al., 2016), atmospheric CO_2 concentration (Sakurai et al., 2009) and vapor pressure deficits (Ray et al., 2002). Extreme weather events like drought for instance have exhibited an increasing trend (Mazdiyasni et al., 2015) resulting in crop production decrease (Lesk et al., 2016; Zipper et al., 2016). Output/result like these provide vital information for mitigation strategies, early warning, prediction system and drought monitoring designed to improve crop yield and resilience against droughts (Hao et al., 2014; Aghakouchak et al., 2014). In the same manner, adaption measures like switching to an existing crop variety, development of new crop varieties, changes in crop growing pattern as well as shifting planting dates may shaping the severity and modulate the negative effect of climate on crop production and yield (Challinor et al., 2014; Cohn et al., 2016). It is expedient that farmers want to grow crops in lands with optimal nutrient and water storage conditions, this will result in consequent changes in the spatial pattern of the crop distribution (Guoyong et al., 2017).

1.1.2. Maize and phenology

Although maize has the capacity to adapt to both high temperature and dry environment, global warming still exert considerable negative impacts on maize yield in many regions of the world (Lobell and Field, 2007), thereby reducing global maize by about 4% from 1980 to 2008 (Lobell and Gourdji, 2012). Even though historical warming has helped improve maize yield in some regions (Chen et al., 2012), much more dramatic impacts are speculated on maize yield as well as food security under climate regimes in future: for instance by the end of this century it is expected that the growing season temperatures in the subtropics and tropics will supersede the most extreme temperatures recorded in the past century also the hottest seasons recorded in the temperate regions will represent the future norm in a lot of regions of the world (Battishi et al., 2009). However, in different part of the world higher growing-season temperatures has been seen to be highly detrimental to maize yield and it equally aggravate food insecurity (Derying et al., 2014).

One important component of farm management is the accurate monitoring of crop development pattern (that is the phenology and growth) as it allows the assessment of the most critical stages of growth during periods of favourable weather conditions (Vina et al., 2004). Phenological monitoring also helps to have a better understanding of crop growth processes and development. Additionally, phenological monitoring is important for proper understanding of intra-annual and inter-annual variations of agroecosystems as well as improves yield prediction models. A number of dynamic simulation models have been developed that compute daily crop development and growth, also simulate dry matter production of the plants from emergence to its maturity and finally presenting an estimate of final yield (Sun, 2000). However, these models are not efficient when it comes to its application to non-optional growing conditions (like hail, damaging frost, drought, pests or disease infestation, among others). For these conditions, remote-sensing data can be used to calibrate the models and adjust for possible improvement (Clevers et al., 1994).

Diverse disciplines have adopted the application of remotely sensed dataset (e.g., MODIS, Landsat, and SPOT), as it is readily available, decadal time spans and global coverage (Kerr and Ostrovsky, 2003). Satellite sensors have the capacity to capture numerous physiognomic characteristics of vegetation such as plant moisture content as well as photosynthetic activity using spectral radiance measurements (Tucker et al., 1985). Quite a lot of methods for converting radiance measurements into vegetation indices have been developed based on the band-ratioing of vegetation sensitivity in the visible (VIS) and the near-infrared (NIR) spectral bands. However, normalized difference vegetation index (NDVI) (Parplies et al., 2016) is the most widely used, owing to its ability to describe the crop phenology accurately, its readily available NDVI products (Sehgal et al., 2011), its simple calculation (Huete et al., 2002), and its sensitivity to soil conditions and atmospheric effects compared with other vegetation indexes which makes it useful for describing the vegetation growth process (Johnson et al., 2016). Furthermore, it has been used extensively for drought detection (Sruthi and Mohammed 2015), vegetation monitoring (Nurhussen 2016), crop yield assessment (Mariano et al., 2015) and phenological studies (Elodie et al., 2014).

Additionally, maize phenology can be generally divided into two stages namely: the vegetative stage which is from emergence to tasseling according to the number of fully expanded leaves and the reproductive stage which is from sulking to physiological maturity according to degree of kernel development (Ritchie et al 1992). Several noticeable transitions of great importance to farm managers occurs within these stages some of which include: a) crop emergence that is the date of onset of photosynthetic activity (SOS); b) tasseling that is date when maximum leaf area is reached and maize tassels appear (POP); c) initiation of senescence that is date at which green leaf area evidently begins to decrease (EOS) (Cicchino et al., 2010). In the quest ~~order~~ to maximize yields the plant requires to optimize nutrients supply and maintain a favourable environmental conditions (like precipitation, solar radiation, temperature, soil moisture) preceding every stage. When unfavourable conditions occur between the crop emergence time and when its leaf develops it limits the size of the leaves and eventually amount of photosynthetic biomass. However, when it occurs at the start of its reproductive cycle that is between tasseling and anthesis, there is the likelihood that the crop pollination will be impaired, and the number of fertilized kernels will be reduced (Severini et al., 2011). Further still, when an adverse condition occurs during the grain-filling period that is between anthesis and physiologic maturity stage it led ~~lead~~ to reduction in the size of kernels that can be harvested. Obviously, awareness of the time of tasseling is not only important but it is also expedient to identify the stress-induced abnormalities that occurs during the rapid leaf expansion so as to device corrective measures. Also, early detection of the onset of senescence as a result of disease or water stress preceding the growth stage, is vital because it could directly influence yield.

1.1.3. Maize and drought

Water is required by all organism (of which maize is not an exception) in a stipulated quantity, treat is posed when there is deficit in the required amount. To determine water deficit in plant it is necessary to evaluate the optimal plant water requirement. Water requirement for maize production is not static throughout its growth stages, at its initial growth stage low amount of water is required then eventually reaches the peak at reproductive growth stage and decreases again during its terminal growth stage (Aslam et al., 2015). A single maize plant at the reproductive stage requires about 8-9mm of water per day. Water is required critically two weeks before and two weeks after pollination during maize production. This is because pollination is the stage at which the grain yield is determined. Also, soft dough formation and grain filling are extremely sensitive to water deficit, while physiological maturity and pre-tasseling are comparatively obtuse to water shortage. The implication of drought stress during the vegetative stage is that rate of growth reduces (Pannar 2012). A total of about 450-600mm is required throughout the whole season and for every millimeter of water about 15.00kg of kernels is produced (Du Plessis 2003). From maize plant emerge up to its maturity stage about 250litres of water is consumed (Du Plessis 2003). Furthermore, any imbalance in the following traits disturb the plant water relation: water potential, relative water contents, stomatal resistance, transpiration rate, and leaf temperature as all these maintains the plant water relation (Anjum et al., 2011). The relative water contents is responsible for determining the status of metabolic activities of the tissue or cell. Also, the relative water contents of the leaves are higher at the early leaf development and this tend to decline as the plant approaches maturity. According to Siddique et al., (2001) there is a strong correlation is reported between water uptake, relative water contents and transpiration rate. Under drought stress, water potential and relative water contents is reduced, resulting in an increase in leaf temperature owing to the reduction in the transpirational cooling (Siddique et al., 2001). One can easily perceived that plant water status is reliant on stomatal activity (Anjum et al., 2011).

One global climatic phenomenon that affect humanity in numerous ways is drought, it can lead to crop failures resulting from famine which causes food shortages leading to malnutrition and health issues that eventually leads to loss of life (Masih et al., 2014). Further still, it causes massive environmental damage and it is considered as the main cause of desertification, land degradation and aridity. According to the drought impact estimate from 1900-2013 by EM-DAT (2014), about 642 drought events have been reported worldwide leaving about 12 million people dead and over 2 billion been affected. Two critical environmental factors that regularly influence plants growth and development are temperature and water. Drought causes wide economic damage to agriculture (NCDC 2011), an effect that could increase with progress in global climate change (Keane et al., 2009). The negative impact of drought on agricultural production is anticipated to likely aggravate in the future with an increase in frequency, erratic and intensity of this event (Sanderson et al., 2011). To compound this problem, there as being continues decline in the fresh water and land used for agricultural use at an unmanageable rate (US CCSP 2008). As projected by UNEP GRID-Arendal 2009 cropland could be reduced by 8% to 20% by 2050. Subsequently, agricultural production is bound to be faced with challenges of water deficit/limitation and unfavorable environmental conditions, emphasizing the essence for a comprehensive and fully incorporate approaches to sustain and improve agricultural productivity in the future (Delgado et al., 2011).

The vulnerability of maize plant to drought and heat cannot be overemphasis, according to FAO STAT 2006-2008 and Lobell et al 2011b an average of about 15% to 20% of the potential world maize production is lost to these stresses on a yearly basis. The overall loss is highly dependent on the stage of the plant when the stress occurs, the duration of the stress and the severity of the stress (Heiniger 2001). South Africa, being the major maize producer in Africa, is battling with one of the worst droughts ever recorded, this commence in early 2015 (CEC 2016). As recorded by the South African Weather Service, the year 2015 was the driest in South Africa since 1904. Ever since the year 1904, an average of 608 mm per annum of rainfall as been received in the nine

Province, but in 2015 an average of about 66% of the annual average (403 mm) was received in the country. Before this the lowest ever recorded was in the 1945 when about 437 mm per annual (72%) was received. The land available for maize production in South Africa as equally change over the years, for instance 10-year record average revealed that approximately 2.5 million ha of land is used for planting maize annually, out of which 1.5 million ha is used for white maize and the remaining 1.0 million ha is used for yellow maize (Grain SA 2016). Conversely, there is a slight difference in the 2015/16 production season (equivalent to 2016 calendar year), estimated area used for commercial maize production was about 1,947 million ha. This is a reduction of about 26.6% or 706,100 ha less than that of the previous season (2015) where an estimate of about 2,653 ha of land was used for maize production. There was also variation in the maize production of that of 2015 which is estimated at 9,955 million tons compared to that of 2016 which is estimated at about 7,161 million tons 28.07% (2,794 million tons) less than the previous season 2015, and 49.75% (7,089 million tons) less than that of 2014 planting season which was estimated at 14,250 million tons. These decreases are associated with severe drought conditions that occurred in the major maize producing areas of South Africa.

1.1.4. Maize yield prediction

One of the crucial goals of agricultural production is to achieve maximum crop yield at little or no cost. To attain the point whereby yield is increasing, and profit is made on the produce, it is important that problems associated with crop yield indicators are detected and managed early (Dahikar et al., 2014). With predictions crop managers could minimize losses resulting from unfavourable conditions. Predictions could also be used to maximize crop production when there is a likelihood for favourable growing conditions. It has been of great interest for agro-meteorologists researcher to predict strategic plants crop yield such as rice, wheat, corn because they are of national and international economic importance. The need therefore arises for an accurate prediction mechanism using meteorological data. Presently, lots of yield prediction models exist, classified mainly into two groups namely: Crop Simulation Models example which include CERES (Jones and Kiniry, 1986) and Statistical models. However, of recent application Artificial Intelligence (AI) like Artificial Neural Networks (ANN), Genetic Algorithm and Fuzzy Systems has proven to be more competent in dissolving the problem. These application makes models more accurate and easier than the natural systems which is more complex requiring many inputs.

The complexity of factors affecting crop yields like weather, management and soil, makes it practically impossible to get a precise result by using traditional statistics. Years back researchers used process-based or empirical tools to investigate the causes of yield variability and detect the various yield-limitation factors within fields. However, ANN is an automatic learning tool which is an attractive substitute for processing the enormous dataset produced by precision farming production and research (Khairunniza-Bejo et al 2014). Also, with ANN yield losses due to yield limiting factors can be estimated. Furthermore, ANNs require no explicit mathematical equation and no limiting assumptions of linearity or normality contrast to the analytical approaches (MathWorks, 2005). Unlike the traditional physiology-based crop models, most of the intense computations take place during the training process in ANN. Its ability to provide solution to lots of problems linear system is incapable of resolving, makes ANN essential especially in originating and developing better invention for the society. For relative fast and rapid unknown input identification in a real-time environment, ANN is trained for a particular system (Keller et al., 1994). Furthermore, ANN have been applied in a wide range of data processing applications like land use change/classification (Shock et al., 2002), land drainage engineering (Yang et al., 1997), crop evapotranspiration calculation (Odhiambo et al., 2001), predict yield for a new set of input conditions (Liu et al., 2001), and image recognition (Noh et al., 2004).

The capability of ANN to predict, forecast and classify in biological science field has made it famous among many authors (Shearer et al., 2000; Kaul et al., 2005). Also compare to regression model an ANN model is more reliable and precise for crop yield prediction (Kaul et al., 2005). To capture the principle of significant associations, it is important that a well-trained ANN model comprise the main factors that quantify the essential variability related to crop production. A neural network like human nervous system processes information. Similar to human nervous system which comprise of interconnected neurons, an ANN consist of interconnected information processing units (Riedmiller et al., 1993). It is a model that uses an activation function through interconnected information processing units to convert input into output. ANN first receives the raw input, processes it and then transfers the processed information to the hidden layers. The hidden layer further passes the information to the last layer, where the output is produced. ANN is quite adaptive in nature, it learns from the provided information (that is trains itself from available data), which is regarded as the known outcome which optimizes its weights for an improved prediction in a scenario with unknown outcome (Anastasiadis et al., 2005).

1.2. Maize production

1.2.1. Global maize production

Asides rice and wheat, maize is the third largest crop produced globally. Although it is usually used and traded as a prominent feed crop, it is also an essential staple food. Asides feed and food, maize is likewise used for manufacturing ethanol. It is one of the ancient human-domesticated plants. Its origin can be trace as far back as 7000 years ago, when it was just grown as a mere wild grass called teosinte in Central Mexico (Piperno et al., 2001). Eventually it was recognized has a major food crop, over time native Mesoamerican succeeded in improving the crop, by analytically selecting some varieties for their desired traits. This process gradually transforms teosinte to its present state known as maize, a name derived from "mahis" which means "source of life" by the Tanio people who have mastered the cultivation of the crop (Milazzo 1986). It is also referred to as corn in the United States, which is the world's largest producer, exporter and consumer of maize. The important properties such as been an annual crop with high productivity and its geographic adaptive ability makes maize a globally cultivated crop. Maize has several hybrids with each of them having its own unique properties and kernel characteristics; the most famous ones are: **dent** (also known as field maize, used for livestock feeding, available in white and yellow species), **flint** (also known as Indian maize, produced mostly in South and Central America), and sweet (also known as green maize) (Nuss et al., 2010).

Maize is classified based on its taste and colour, it is however broadly categorized into two groups namely white and yellow. The yellow maize constitutes majority of the whole maize production worldwide as well as the international trade (Ranum et al., 2014). It is mostly produced in countries situated in the northern hemisphere where it is conventionally used for animal feed. White maize requires a more favourable climatic conditions for its production, it is grown in just a few countries among which are Mexico, southern Africa and in the United States. White maize is considered generally as food crop and it is more expensive than its yellow counterpart. The assumed rise in global maize consumption that was abated in 2008/09 has subsequently regained its momentum, with the increase in industrial usage which arguments the periodic irregular demand for animal feed (Economist Intelligence Unit (EIU) 2010). Furthermore, EIU predicted an increase of about 805 million MT (Metric Tonnes) in global maize consumption in 2009/10, a rise of 3.4% from 2008/09. Assumption of ethanol production increases and an upswing demand in feed for some countries, as lead to a further speculated increase of about 1.7% (818 million MT) in 2010/11. According to Table 1 below showing the world record of maize production from 1994 to 2004 by FAO, the record revealed that China had the highest maize production in Asia, South Africa topped the list for Africa, it is Mexico for Central America, Brazil for South America, United State of America (USA) for North America and European Union consisting about 15 countries for Europe. Over all the world's largest maize producer is USA, and the developed countries contribute largely to global maize production.

Table 1-1: Maize Production (million tonnes)

CONTINENT/COUNTRY	1997	1998	1999	2000	2001	2002	2003	2004
ASIA	143.4	174.8	170.1	149.0	158.9	165.4	167.2	183.6
China	104.6	133.2	128.3	106.2	114.3	121.4	115.9	130.3
India	10.8	10.7	11.5	12.0	13.2	11.2	15.0	14.2
Indonesia	8.8	10.2	9.2	9.7	9.3	9.6	10.9	11.2
Iran	0.9	0.9	1.2	1.1	1.1	1.4	1.7	1.5
Korea	1.0	1.8	1.2	1.0	1.5	1.7	1.7	1.7
Kyrgystan	0.2	0.2	0.3	0.2	0.4	0.4	0.4	0.5
Myanmar	0.3	0.3	0.3	0.4	0.5	0.6	0.7	0.8
Nepal	1.3	1.4	1.3	1.4	1.5	1.5	1.6	1.6
Pakistan	1.5	1.7	1.7	1.6	1.7	1.7	1.9	2.8
Philippines	4.3	3.8	4.6	4.5	4.5	4.3	4.6	5.4
Thailand	3.8	4.6	4.3	4.5	4.5	4.2	4.2	4.2
Turkey	2.1	2.3	2.3	2.3	2.2	2.1	2.8	3.0
Viet Nam	1.7	1.6	1.8	2.0	2.2	2.5	3.1	3.4
AFRICA	41.3	41.0	42.1	44.8	41.0	42.4	45.0	45.0
Egypt	5.8	6.3	6.1	6.5	6.8	6.4	6.5	6.7
Ethiopia	2.3	2.8	2.7	3.3	2.8	2.8	2.7	2.4
Kenya	2.2	2.4	2.3	2.2	2.8	2.4	2.7	2.6
Malawi	1.5	1.8	2.5	2.5	1.6	1.6	2.0	1.7
Mozambique	1.0	1.1	1.2	1.0	1.1	1.2	1.2	1.4
Nigeria	5.3	5.9	5.5	4.1	4.6	4.9	5.2	5.6
South Africa	10.1	7.7	8.0	11.4	7.8	10.1	9.7	9.7
Tanzania	1.9	2.8	2.5	2.0	2.6	2.7	2.9	3.0
CENTRAL AMERICA	20.4	21.3	20.8	20.8	23.4	22.6	24.2	25.0
Mexico	17.7	18.5	17.7	17.6	20.1	19.3	20.7	21.7
SOUTH AMERICA	58.2	55.1	51.4	55.8	64.9	57.7	71.6	65.6
Argentina	15.5	19.4	13.5	16.8	15.4	14.7	15.0	15.0
Brazil	36.2	30.2	32.0	32.3	42.0	35.9	48.3	41.8
Chile	0.9	0.9	0.6	0.7	0.8	0.9	1.2	1.3
Colombia	1.0	0.8	1.0	1.2	1.2	1.2	1.2	1.4
Peru	0.8	0.9	1.1	1.2	1.3	1.3	1.4	1.2
Venezuela	1.2	1.0	1.1	1.7	1.8	1.4	1.8	2.2
NORTH AMERICA	241.0	256.8	248.7	258.7	249.9	236.8	265.9	308.7
Canada	7.2	9.0	9.2	6.8	8.4	9.0	9.6	8.8
United States of America	233.9	247.9	239.5	251.9	241.5	227.8	256.3	299.9
EUROPE	81.3	66.5	72.6	62.8	76.1	75.5	69.5	96.4

European Union 1/	39.4	36.4	37.1	38.3	41.0	40.5	33.7	54.9
Romania	12.7	8.6	10.9	4.9	9.1	8.4	9.6	14.7
Russian Federation	2.7	0.9	1.1	1.5	0.8	1.6	2.1	3.5
Ukraine	5.3	2.3	1.7	3.8	3.5	3.1	6.9	8.9
Yugoslavia Fed. Rep.	6.9	5.2	6.1	2.9	5.9	5.6	3.8	6.6
OCEANIA	0.6	0.5	0.5	0.6	0.5	0.6	0.5	0.6
WORLD	586.3	616.0	606.3	592.5	614.7	601.0	643.9	725.0
Developing Countries	252.2	283.4	275.1	257.9	279.1	276.5	296.7	307.7
Developed Countries	334.2	332.5	331.2	335.6	335.6	324.5	347.2	417.2
LIFDCs 2/	168.0	200.4	196.7	174.1	183.9	189.0	192.6	208.7
LDCs 3/	15.4	17.2	18.5	18.5	18.1	18.3	20.7	20.2
NFIDCs 3/	13.4	13.9	13.9	15.0	16.0	14.9	16.0	17.3

Source: FAO

Note: Information as of November 2006. Data are compiled on a July/June basis.

1/ Up to 2003/04 15-member countries, from 2004/05 25-member countries.

2/ Low Income Food Deficit Countries (LIFDC) refer to food deficit countries with per caput income below the level used by the World Bank to determine eligibility for IDA assistance (i.e. US$1 415 in 2002).

3/ The Least Developed Countries (LDC) and Net Food Importing Developing Countries (NIFDC) groups include a list of countries agreed by the World Trade Organization (WTO) to qualify as beneficiaries under the Marrakech Decision on the Possible Negative Effects of the Reform Programme on LDC and NFIDC.

1.2.2. Regional maize production

Maize contribute about 36% of the total caloric consumed from cereals across southern Africa, it is the most vital basic food crop and cereal in the region. It is much noticeable among the rural, poorer population where it accounts for much greater percentages. Aside being consumed directly by human, it is equally an essential input for animal feed production as well as an intermediate product for industrial use as constituents of oil or other food products (Myers et al., 2012). This does not only make maize a crucial part of food security of the region, but it is also a dominant driver of the systems that support agriculture wholly, by providing the platform for efficient grain trade. In addition, it provides avenue for main market services such as supply, commodity exchanges, storage, equipment supply, extension and agricultural finance which are required for the provision of fabric of a commercial agricultural system. Maize produced in southern Africa is between 18-24 million tons on a yearly basis, of which 55% is from South Africa, subject to rainfall in the area (Grant et al., 2012). The total maize consumed in the region per annual is about 17 million tons, most of the years southern Africa is a net surplus producer. Although several countries in this region are regularly in net deficit like Zambia, Botswana, Namibia, Mozambique and Angola while others usually have a stable surplus such as Malawi, Zambia and South Africa. The food surpluses/deficits within this region are often argument by long term storage as well as the regional and international trade.

Majority of the maize produced and consumed in southern Africa are white. In all the region, only South Africa produces yellow maize in a substantial capacity and used predominantly for livestock feed. According to Corsino 2016 the trade flows within the region basically reveal high trade in white maize. For the last 30 years growth in maize production in southern Africa was primarily due to increase in area cultivated for maize production. In this region maize production is highly dependent on rainfall (rain-fed maize production), leading to unstable output year by year. However, there is the speculation from Grant, Wolfaardt and Louw, (2012) that food consumption patterns in Africa are likely to have a dramatic change in the coming decades, this is associated to change in the consumption patterns of household within the region – triggered by the growing per capita income and increase in urbanization. Population growth as being identified as the major determinant of maize consumption in southern African development community (SADC) apart from South Africa (Grant et al., 2012). There is an expectation for maize consumption to remain fairly constant in future with an expected per annual growth rate of 0.51% between 2009/2010 to

2013/2014 production periods (Grant, et al., 2012). Maize production in southern Africa between 2007 to 2011 (Table 2) revealed that South Africa is the largest producer in southern Africa and Malawi is the second largest maize producer and lowest production comes from Botswana.

Table 1-2: Maize Production in southern Africa (thousand tonnes)

Country	2007	2008	2009	2010	2011
Angola	700	642	1,200	1,250	1,250
Botswana	12	2	7	17	18
Malawi	3,226	2,634	3,777	3,415	3,646
Mozambique	1,380	1,534	1,710	1,932	1,880
Namibia	61	60	60	60	60
South Africa	6,947	7,339	13,164	12,567	13,421
Zambia	1,425	1,366	1,446	1,889	2,800
Zimbabwe	900	700	525	650	1000
Regional totals	14,651	14,277	21,889	21,780	24,075

Source: *BMI USDA: Business Monitor International Country reports Southern Africa Agribusiness Report Q1 2012 (extracted from USDA Table 1, data from SAGIS and CEC*)

1.2.3. National maize production

Maize is concerned of utmost importance in South Africa, it is the second major crop produced in the area next to sugar cane. Owing to its multiplier effects, the maize industry is essential to the economy benefiting both the employer and the foreign currency earner, since maize also used as raw material for manufactured products like medicine, processed food, paper, textiles, and paint. It is consumed mainly as second-cycle produce in the developed countries, like in form of eggs, dairy products and meat. However, it is consumed directly in the developing countries, serving as staple diet for about 200 million people. Although, Maize is produced throughout the country but under diverse environmental conditions. Free State, Mpumalanga and North West Provinces are the largest producers in the area, contributing about 83% of the total production in the country. Grain production in South Africa is divided into 36 regions. Region 1 to 9 comprise of the winter rainfall areas (i.e. Eastern Cape, Karoo and Western Cape), maize is not produced on a commercial scale in these regions. Region 10 is Griqualand West and region 11 is Vaalharts both in the North West. Furthermore, region 12 to 20 are all located in the North West Province. Regions 21 to 28 contributed about 62% of the total maize production in South Africa during 2009/10 production season, they are located in the North West and Free State. Region 29 to 33 located within Mpumalanga which happens to be the second largest maize producing Province in the country. Region 34, 35 and 36 falls within Gauteng, Limpopo and KwaZulu-Natal respectively (DAFF, 2012).

In South Africa around 8.0 million tons of maize are produced annually on land of about 3.1 million ha, half of which is white maize human consumption. The maize industry in South Africa is divided into developing and commercial agriculture. There is an estimate of about 9,000 farmers involved in commercial maize farming employing about 150,000 farm workers while the number of farmers involved in developing agricultural are unknown. 98% of the maize produced in the country is produced by commercial agriculture while the rest 2% is produced by the developing agriculture. As reported by DAFF 2012, 40% of all the commercial maize in South Africa during the 2009/2010 season was from Free State Province. North West Province on the other hand contributed 22% closely followed by Mpumalanga Province which produced 21% and Northern Cape Province produced 5% of the entire commercial maize grown in the country. The 2013/14 planting season recorded the highest maize production and yield per hectare in South Africa (Figure 1). Low production was record in 1991/92, 1994/95, 1997/98, 2000/01, 2005/06, and 2015/16 these could be likely as a result of reduction of land available for maize production because several changes in area available for maize production occur during these periods, fluctuation in climatic variable, drought incidence, farm management practice etc.

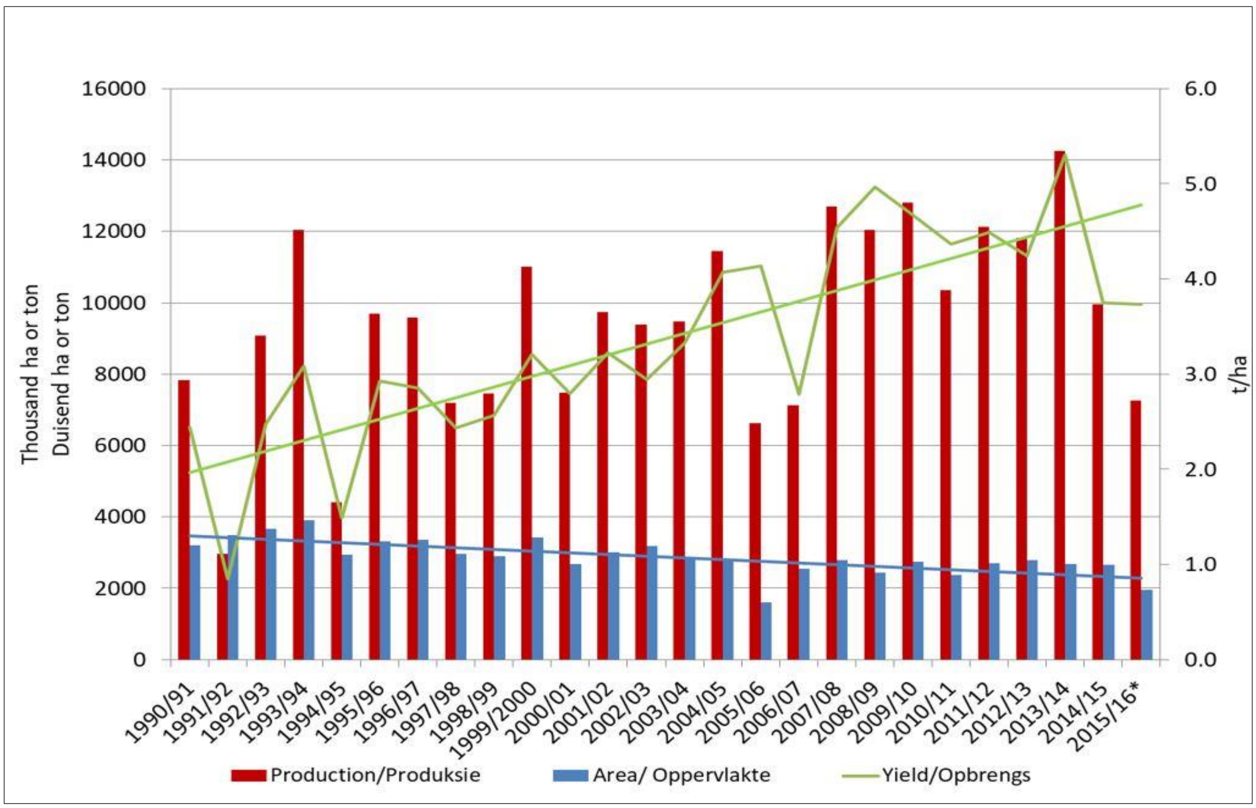

Figure 1-1: Total area planted, production and yield of maize in South Africa
***Source:** Grain SA*

1.2.4. Maize production in the four major maize producing province (Study area)

In South Africa white maize is an indispensable food, it is used in form of whole grains, green mealies and meal and it is also processed into cereal and snack. Furthermore, it is of great use to the livestock industry, snack industry and millers. White maize as well as yellow maize can be used as livestock feed for silage or hay. The yellow maize significantly contributes to dairy products and red and white meats production. Maize is given different names in South Africa such as mafela, mmidi, mavhele, mielies, mmopo, umbila, umbona (DAFF, 2008). The producing areas in South Africa is shown in the Table 3 below:

Table 1-3: Maize producing district of South Africa

Province	District
North West	Bojanala, Ngaka Modiri, Malema, Dr Ruth, Segomodi Mompati
Mpumalanga	Gert Sibande
Free State	Motheo, Lejweleputswa, Thabo Mofutsanyane, Northern Free State
KwaZulu-Natal	uMgungundlovu, UGu
Gauteng	Sedibeng, Metsweding, West Rand
Northern Cape	Kgalagadi, Frances Baard

Source: *DAFF 2008*

In South Africa about 90% of maize is produced under dry land condition while the remaining 10% is produced under irrigated conditions (DAFF, 2015). Rain-fed grain cropping area of South Africa is divided into four major maize production regions in conjunction with their climatological characteristics. They are as follows:

- ✓ The Cold Eastern Region (the Mpumalanga Highveld and eastern Free State)
- ✓ The Warm Western Region (western parts of the Free State and most of the North West)
- ✓ The Temperate Eastern Region (Gauteng and the central parts of the Free State)
- ✓ The KwaZulu-Natal Region (the western/upland and central/midland parts of KZN)

The major maize producing areas are located within these regions cutting across the western and central parts of North West, southern Gauteng, the central to south-western parts of Mpumalanga and the north-western part of Free State. Precipitation ranges between 550 and 650 mm in the west of these major maize growing areas. Precipitation is relatively unpredictable and has a great influence on crop production in the area. Even though the beginning and duration of the rainy season in this region limit the length of the growing season, the high heat units enable its suitability for crop production and the growth of white maize varieties. Furthermore, the central and eastern parts of this area (that is Gauteng and Mpumalanga) receive more rainfall than the west, the mean annual rainfall in the area ranges between 650 and 850 mm. The result of low heat units in the area is a relatively short growing season which is quite suitable to produce yellow maize varieties.

Maize production in South Africa is concentrated in Free State, North West, Mpumalanga and KwaZulu-Natal Provinces contributing about 34%, 32% 24%, and 3% respectively to the total maize production in the country. Majority of the maize produced in Mpumalanga (67%) are yellow maize while majority of those produced in North West as well as Free State are white maize. Yellow maize contributed 68% of the total maize production in Mpumalanga while the majority of maize produced in the Free State (54%) and especially the North West (72%) Province is white.

1.3. Research problem, rationale and questions

1.3.1. Research problem and rationale

The usefulness of maize cannot be overemphasis, it has been named as the most important crop in South Africa, used for human consumption, industry purposes, it is also indispensably important in both the local and international market. On-going climate change will indisputably hamper agricultural output and contribution of the agricultural sector to South African's gross domestic production (GDP) and food security, therefore potentially destabilizing the country with potential spread to the South African Development Community (SADC) region. This implies that, climate change's influence on maize production in South Africa can no longer be underestimated, given the ultimate consequences of such impacts. Maize is not exempted from the vulnerability of climate change. A little change in climate can either increase or reduced its yield. Previous studies on the potential impact of climate change on field crop production in southern Africa indicated that different crops respond differently to the envisaged change in climate. (Schulze et al., 1993; Chipanshi et al. 2003; Fischer et al., 2005; Thornton et al. 2011). Schulze et al., (1993), developed an analysis tool to simulate primary productivity and crop yields under different climatic conditions in southern Africa. The results reported an overall increase in potential maize production that corresponds to an increased carbon dioxide and temperature conditions. Du Toit et al. (2001) assessed the vulnerability of maize production to climate change in South Africa and found that maize production in the country is characterized by high variations in crop yield that manifest from changes in seasonal precipitation. Gbetibouo and Hassan (2005) used a Ricardian model to assess the impacts of climate change on seven field crops (maize, wheat, sorghum, sugarcane, groundnut, sunflower, and soybean) in South Africa. The authors reported that the production of field crops was sensitive to marginal changes in temperature than to changes in precipitation, whereby an increase in temperature positively affects the net revenue whereas a reduction in rainfall negatively affect the net revenue. Similar studies by Deressa et al. (2005) alluded that climate change has significant nonlinear impacts on the net revenue of sugarcane production in South Africa, with higher sensitivity to increasing temperature than precipitation. Maize is one of the rain-fed summer field crops grown in South Africa with a 3% annual increase in demand (Durand 2006). With the evident change in climate hence the need to study the effect that fluctuation in climate variables has on maize yield, determine the duration and time taken by plant canopy to be photosynthetically active, long-term trends in climate as well as short-term climatic variation. Hence, the spatio-temporal characterization of agro-climatic patterns across maize producing provinces to determine the most dominant climatic parameter influencing maize production will help farmers towards achieving proper climate adaptation and mitigation practices by farmers, in a bid to minimize the adverse effects of climate change on maize production. In addition, maize phenology is climate dependent. The estimation of variation in phenological which are induced by climate change can allow for more accurate predictions of the timing of planting crops and help improve managerial decisions, through the provision of phenological parameters (such as; start of season (SOS), end of season (EOS), length of the season (LOS), maximum NDVI during the season. It therefore become crucial to investigate the changes in the phenology metrics in relation to maize yield and the potential factors that stirred the changes across the maize producing Provinces of South Africa. The determination of length of growing period is therefore essential to determine the variability of maize phenology in response to climate. Also, important is the impact of extreme weather events such as droughts which as synonymous with climate change on maize production. Drought conditions pose serious challenge to the vegetative and reproductive stages of maize having the capacity to reduce potential maize yield by 25-50%. Therefore, effective monitoring of drought can provide an efficient drought early warning and predict maize production to have a foresight of future expected yield if farmers does the needful.

1.3.2. Research questions

Certainly, farmers habitually grow crop in lands with optimum water, nutrient storage conditions and climatic conditions, resulting in subsequent changes in crop yield. Hence, a vital question arises to how maize yield will respond to the historical changes in climate, phenology and climate extremes such as drought? This further leads to other research questions such as: What are the major climatic drivers of changes in maize production across the maize producing Provinces? What is the optimum LOS and SOS for optimum yield? What drought condition is more critical to maize yield and at what geographical location and time?

1.4. Aim and objectives

1.4.1. Aim

The overall aim of the study is to examine the variation in maize yield and develop a framework for predicting maize yield in response to climate change.

1.4.2. Objectives

The specific objectives of this study are to;

1. Determine the impact of agro-climatic parameters on maize production.
2. Determine the changes in the satellite derived phenological parameters and its relationship with maize production.
3. Investigate the influence of drought on maize production.
4. Predicting maize production using neutral-network analysis.

Objective 1 is achieved with the first publication titled: Analysis of agro-climatic parameters and their influence on maize production in South Africa (Available online: https://link.springer.com/article/10.1007/s00704-017-2327-y). **Objective 2** is achieved with the second publication titled: Variability of satellite derived phenological parameters across maize producing areas of South Africa (Available online: https://www.mdpi.com/2071-1050/10/9/3033 manuscript ID number ***sustainability-280129***). **Objective 3** is achieved with the third paper titled: Analysis of drought conditions over major maize producing provinces of South Africa yield (accepted for publishing with Journal of Agricultural Meteorology). While **objective 4** is achieved with the fourth paper titled: Application of artificial neural network for predicting maize production (Available online: https://www.mdpi.com/journal/Sustainability 2019, 11, 1145 manuscript ID number **sustainability-422883**). Besides the publication for the four main objectives, the literature review of this study is currently under review with journal of Agricultural Research for publication. Therefore, a minimum of 5 publications are expected from this study.

1.5. Study area

Figure 2 shows the location of the study area comprising of the major four maize producing provinces of South Africa. The provinces include Free State (FS), North West (NW), Mpumalanga (MP), and KwaZulu-Natal (KZN) located in the north-western and north-eastern part of South Africa between 22° E to 33° E and − 32° S to − 24° S longitude and latitude, respectively. The four provinces accounts for approximately 83% of the total maize production is South Africa. FS and NW provinces are the highest maize producers, contributing more than 60% of the total maize production in South Africa, followed by Mpumalanga (~24%) and KZN (less than 5%). Administratively, FS, NW and MP provinces are landlocked, sharing borders with the Gauteng province in the north, east and west respectively, the Northern Cape province in the west for both FS and NW.

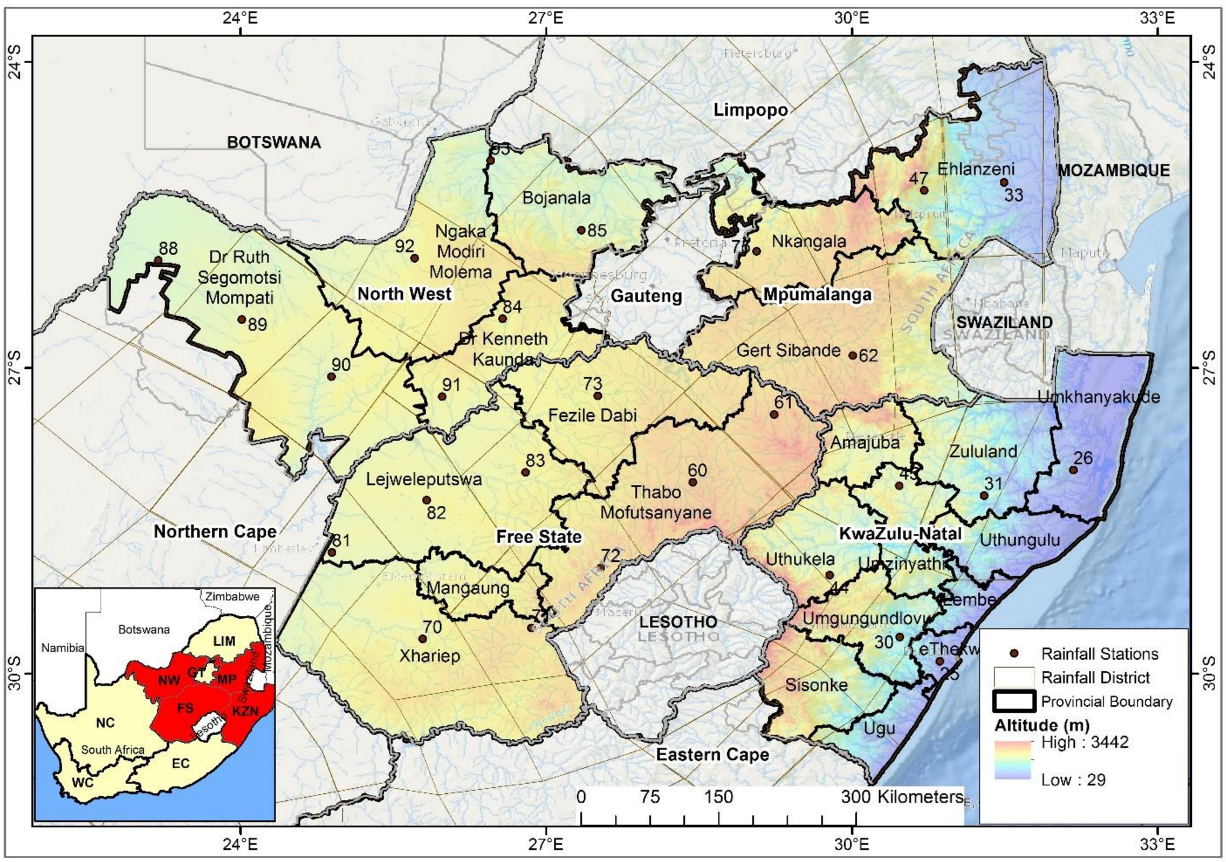

Figure 1-2: Location of the study area, showing the rainfall stations overlaid with SAWS district rainfall and elevation (m)

FS share border with Lesotho and KZN in the east and the Eastern Cape province in the south while NW and MP share border with the Free State Province in the south, the Limpopo province in the north east and north respectively and Botswana in the north for NW, Swaziland in the south-east and Mozambique in the east for MP. On the other hand, KZN, shares border with the Indian Ocean to the east, Swaziland and MP province to the north, the FS province in the west, Lesotho in the south-west and the Eastern Cape Province in the south. The four provinces consist of 23 district municipalities FS (5), MP (3), NW (4), KZN (11), 2 metropolitan municipality and 106 local municipalities. Vast area of the province is predominantly rural with most of the people relying on agriculture for their livelihoods. Climatically, as classified by Koppen climate classification (Kottek et al., 2006), climate conditions within the study region range between cold, temperate, and subtropical conditions. Rainfall exhibit seasonal distribution, with all the four selected provinces receiving summer rainfall. Particularly, the NW and FS provinces receive total annual rainfall of less than 500 mm whereas Mpumalanga and KZN receive between 500 and 800 mm. The annual mean maximum temperature for the four Provinces is 25 °C, while the annual mean potential evapotranspiration is 3.7 mm/day. Large-scale commercial forests, fruits, and vegetable farms dominate a large proportion of the farms across the provinces however with pockets of small-scale and subsistence livestock and rain-fed maize farming which play a crucial role in the improvement of livelihoods and food security in the provinces and are more susceptible to the impact of climate change due to low or lack of mitigation and adaptation capacity (DWAF 2012).

1.6. Data and Sources

Summary of the datasets and their sources used in this study is given table 4.

Table 1-4: Summary of all datasets and sources utilized in this research

Data	Source	Time span
Maize (production, land and yield)	Department of Agriculture, Forestry and Fisheries South Africa	1986-2017
Gridded climate dataset (Precipitation, potential evapotranspiration, mean temperature, monthly average daily minimum temperature, monthly average daily maximum temperature)	Climate Research Unit	1986-2017
Normalised difference vegetation index (NDVI)	MODIStsp: MODIS satellite data (United States Geological Survey)	2000-2017
Soil moisture	European Space Agency	1986-2017

1.7. Data analysis

Following the publication style adopted for this research, each publication (objectives) has its data analysis section which are well captured there in.

1.8. Key concepts and conceptual framework

The conceptual framework used for this study form the bases for the phases of the research and the overall outcome; the empirical maize yield predicting system. The framework, as shown in figure 3 consists of four major components: (1) The climatic variables, (2) phenological variables, (3) drought characteristics, and (4) maize yield.

1. Climatic parameters such as solar radiation, air humidity, precipitation, temperature, potential evapotranspiration, and wind speed, often determine the global distribution and productivity of crops and livestock (Ajadi et al. 2011). Hence, climate change and variability are foreseen to have direct and indirect effects on the existing agricultural production systems. This potentially threatening local, regional and/or global food security (Ajadi et al. 2011), depending on the spatial scale of the change. The trend and level of impact due to climate change and/or variability is region dependent (Dastane 2013). The agro-climatic variables used in this study include (Precipitation, maximum and minimum temperatures, potential evapotranspiration and soil moisture). All the variables were acquired from gridded climate dataset, the Climate Research Unit Time-Series 3.24.01 (CRU TS 3.24.01) while the soil moisture data was acquired from the European Space Agency. South African Weather Service's (SAWS) weather station data are used to validate the results.
2. Phenological: The estimation of variation in phenologically induced climate change and variability can allow for more accurate predictions of the timing of planting crops and help improve managerial decisions, through the provision of phenological parameters (such as; start of season (SOS), end of season (EOS), length of the season (LOS), maximum NDVI during the season). The phenological parameters will be derived from MODIS NDVI data (MOD13Q1).
3. Drought: Water is an essential need for every organism in specific proportion. A shortage or a surplus in that particular proportion imposes stressful conditions on the maize (Zdenek, 2017). Water requirement for maize varies across the different growth stages. Drought conditions over the period of about three decades are characterized using the Standardized Precipitation Index (SPI: McKee et al 1993), and the Standardized Precipitation Evapotranspiration Index (SPEI: Vicente-Serrano et al., 2010) drought indices.
4. Maize yield: Maize yield is calculated from the division of total production by area of cultivated acreage.

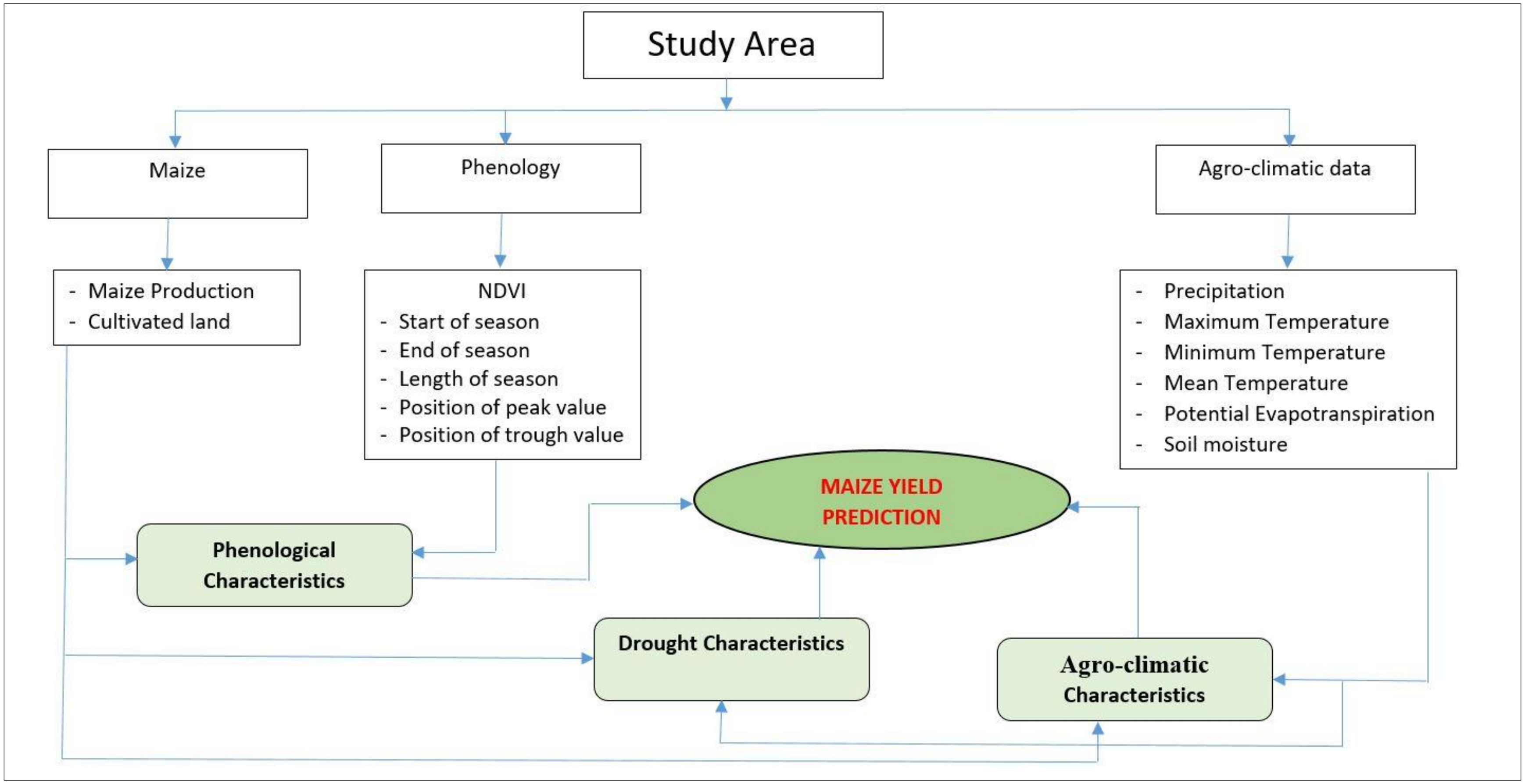

Figure 1-3: Conceptual framework diagram for the study

1.9. Summary

This chapter gave a brief history of maize, the most suitable condition for its growth and its usefulness domestically, industrially and otherwise. This chapter went further to explain the effect of climate change on maize production, the importance of phenological monitoring on maize production and how remotely sensed dataset can help achieve this. Further still, the vulnerability of the crop to drought was discussed as well as the need for prediction of the crop. Then an overview of maize production was given globally, regionally, nationally and locally in South Africa. It also provided the research problem, rationale and research questions were enumerated which was answered in this research. The purpose of the study was pointed out alongside its objectives.

References

1. Aghakouchak, A. 2014. A baseline probabilistic drought forecasting framework using standardized soil moisture index: application to the 2012 United States drought. *Hydrol. Earth Syst. Sci*. 18, 2485–2492.
2. Alexandrov VA and Hoogenboom G. 2000. The impact of climate variability and change on crop yield in Bulgaria. *Agric For Meteorol* 104:315–327.
3. Anastasiadis AD, Magoulas GD and Vrahatis MN. 2005. New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing* 64, pages 253-270.
4. Anjum SA, Xie X-Y, Wang L-C, Saleem MF, Man C, Lei W. 2011. Morphological, physiological and biochemical responses of plants to drought stress. *Afr J Agric Res* 6 (9):2026–2032
5. Aslam M, Maqbool M. A, Cengiz R. 2015. Drought Stress in Maize (Zea mays L.): Effects, Resistance Mechanism, Global Achievements and Biological Strategies for Improvement. *SpringerBriefs in Agriculture*. https://www.researchgate.net/publication/285523072.
6. Battisti DS, and Naylor RL. 2009. Historical warnings of future food insecurity with unprecedented seasonal heat. *Science* 323, 240–244.
7. Bindi M, and Olesen JE. 2011. The responses of agriculture in Europe to climate change. *Reg Environ Change* 11:151–158.
8. Cai CZ, Velthuizen HV, Fischer G, Prieler S. 2006. Analyses of maize yield potential by Chinese farming system zoning based on AEZ model (in Chinese with English abstract). *Maize Sci J* 4:158–161.
9. CEC (Crop Estimates Committee) 2016: www.daff.gov.za / Statistics
10. CFIA (Canadian Food Inspection Agency), 2014. The Biology of Zea mays (L.) (Maize). Biology Document No. BIO1994-11. Available at: http://www.inspection.gc.ca/plants/plants-with-novel-traits/applicants/directive94-08/biology-documents/zea-mays-l-/eng/1330985739405/1330985818367. (Accessed on 10 July 2016).
11. Challinor, AJ, Watson J, Lobell DB, Howden SM, Smith DR, and Chhetri N. 2014. A meta-analysis of crop yield under climate change and adaptation. *Nature Clim. Change* 4, 287–291.
12. Chen C, Qian C, Deng A, and Zhang W. 2012. Progressive and active adaptations of cropping system to climate change in Northeast China. *Eur. J. Agron*. 38, 94–103.

13. Chiotti QP, and Johnston T. 1995. Extending the boundaries of climate change research: a discussion on agriculture. *J Rural Stud* 11:335–350

14. Chipanshi AC, Chana R, and Totolo O. 2003. Vulnerability assessment of the maize and sorghum crops to climate change in Botswana. *Clim Chang.* 61(3):339–3360. https://doi.org/10.1023/B:CLIM. 0000004551.55871.eb.

15. Cicchino M, Edreira J, and Otegui M. 2010. Heat stress during late vegetative growth of maize: effects on phenology and assessment of optimum temperature, *Crop Sci*. 50, 1431–1437.

16. Clevers JGPW, Buker C, van Leeuwen HJC, and Bouman BAM. 1994. A framework for monitoring crop growth by combining directional and spectral remote sensing information. *Remote Sens. Environ*. 50:161–170.

17. Cohn AS, VanWey LK, Spera SA, and Mustard JF. 2016. Cropping frequency and area response to climate variability can exceed yield response. *Nature Clim. Change*.

18. Cutforth HW, McGinn SM, McPhee E, and Miller PR. 2007. Adaptation of pulse crops to the changing climate of the Northern Great Plains. *Agron. J*. 99: 1684-1699.

19. Dahikar SS, Sandeep V, Rode SV. 2014. Agricultural Crop Yield Prediction Using Artificial Neural Network Approach. *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering* Vol. 2, Issue 1.

20. Delgado JA, Groffman PM, Nearing MA, Goddard T, Reicosky D, Lal R, Kitchen NR, Rice CW, Towery D, and Salon P. 2011. Conservation practices to mitigate and adapt to climate change. *Journal of Soil and Water Conservation* 66(4):118A-129A, doi:10.2489/ jswc.66.4.118A.

21. Den Elzen MGJ, van Vuuren DP, and Vliet J. 2010. Postponing emission reductions from 2020 to 2030 increases climate risks and long-term costs. *Climatic change* 99: 313-320.

22. Department of Agriculture, Forestry and Fisheries Republic of South Africa. 2008. Maize

23. Department of Agriculture, Forestry and Fisheries Republic of South Africa. 2012. Maize Market Value Chain Profile.

24. Department of Agriculture, Forestry and Fisheries Republic of South Africa. 2015. Abstract of agricultural statistics.

25. Deressa T, Hassan R, Poonyth D. 2005. Measuring economic impact of climate change on South African's sugarcane. *Agrekon* 44(4):524– 542. https://doi.org/10.1080/03031853.2005.9523726.

26. Deryng D, Conway D, Ramankutty N, Price J, and Warren R. 2014. Global crop yield response to extreme heat stress under multiple climate change futures. *Environ. Res*. Lett. 9, 034011.

27. Du Plessis J. 2003. Maize Production. Compiled by Directorate Agricultural Information Services Department of Agriculture in cooperation with ARC-Grain Crops Institute. *Printed and published by the Department of Agriculture and obtainable from Resource Centre Directorate Agricultural Information Services.* Private Bag X144, Pretoria, 0001 South Africa.

28. Du Toit AS, Prinsloo MA, Durand W, and Kiker G. 2001. Report on vulnerability of maize production to climate change and adaptation assessment in South Africa. Agricultural Research Council, Grain Crops Institute.

29. Economist Intelligence Unit. 2010. Global Forecasting Service - Maize. Available at: http://gfs.eiu.com/Article.aspx?articleType=cfs&articleId=77204792 [Accessed September 13, 2010].

30. Elodie V, Agnès B, Christian B, Saad Alexandre, Danny Lo S and Seydou BT. 2014. A Comparative Study on Satellite- and Model-Based Crop Phenology in West Africa. *Remote Sens*. 6, 1367-1389; doi:10.3390/rs6021367.

31. EM-DAT: 2009. The International Disaster Database: http://www.emdat. be/glossary/9#letterd (last access: 13 January 2014).

32. Ewert F, Rounsevell MDA, Reginster I, Metzger MG and Leemans R. 2005. Future scenarios of European agricultural land use. I. Estimating changes in crop productivity. *Agric Ecosyst Environ* 107:101–116.

33. FAOSTAT (Food and Agriculture Organization of the United Nations Statistics Division). 2006-2008. http:// faostat.fao.org/default.aspx.

34. Fischer G, Mahendra S, Francesco NT, and Harrij van V. 2005. Socioeconomic and climate change impacts on agriculture: an integrated assessment, 1990–2080. *Phil Trans R Soc B* 360(1463):2067–2083. https://doi.org/10.1098/rstb.2005.1744

35. Gbetibouo G, and Hassan R. 2005. Measuring the economic impact of climate change on major South African field crops: a Ricardian approach. *Glob Planet Chang* 47(2–4):143–152. https://doi.org/10. 1016/j.gloplacha.2004.10.009

36. Grain SA. 2016:www.grainsa.co.za.

37. Grant W, Woolfaardt A, and Louw A. 2012. Maize Value Chain in SADC Region. Gaborone, Botswana: Southern Africa Trade Hub.

38. Gregory PJ, Ingram JSI and Brklacich M. 2005. Climate change and food security. *Phil Trans R Soc*. 360:2139–2148.

39. Guoyong L and Maoyi H. 2017. Crop yield response to climate change varies with crop spatial distribution pattern. *Scientific Reports* | 7: 1463 | DOI:10.1038/s41598-017-01599-2.

40. Hao Z, and Aghakouchak A. 2014. A nonparametric multivariate multi-index drought monitoring framework. *J. Hydrometeorol*. 15, 89–101.

41. Heiniger, RW. 2001. The impact of early drought on corn yield. Raleigh, NC: North Carolina State University. http://www.ces.ncsu.edu/plymouth/cropsci/docs/early_drought_impact_on_corn.html.

42. Huete A, Didan K, Miura T, Rodriguez EP, and Gao X. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ*. 83, 195–213.

43. Intergovernmental Panel on Climate Change (IPCC), Climate Change: Impacts, Adaptation and Vulnerability, contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge (2007).

44. IPCC. 2007: Summary for Policymakers. In: Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (Eds.).

45. Johnson MD, Hsieh WW, Cannon AJ, Davidson A, and Bédard F. 2016. Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods. *Agric. For. Meteorol*. 218–219, 74–84.

46. Jones CA, and Kiniry JR. 1986. CERES-Maize: A Simulation Model of Maize Growth and Development. *College Station, Texas: Texas A&M University Press*.

47. Kaul M, Hill RL, Walthall C. 2005. Artificial neural network for corn and soybean prediction, Agricultural System 85 1-18.

48. Keane J, Page S, Kergna A, and Kennan J. 2009. Climate change and developing country agriculture: An overview of expected impacts, adaptation and mitigation challenges, and funding requirements. *In* ICTSD–IPC Platform on Climate Change, Agriculture and Trade, Issue Brief

No.2. Geneva, Switzerland: International Centre for Trade and Sustainable Development, and Washington DC: International Food & Agricultural Trade Policy Council.

49. Keller PE, Kouzes RT, and Kangas LJ. 1994. Three neural network based sensor systems for environmental monitoring. In Proc. IEEE Electro94 Conference. Piscataway, N.J.: IEEE.

50. Kerr JT, Ostrovsky M. 2003. From space to species: ecological applications for remote sensing. *Trends Ecol. Evol*. 18 (6), 299–305. http://dx.doi.org/10.1016/S0169-5347(03)00071-5.

51. Khairunniza-Bejo S, Mustaffha S, and Ismail WIW. 2014. Application of Artificial Neural Network in Predicting Crop Yield: A Review. *Journal of Food Science and Engineering*. 4, 1-9.

52. Leng G, Zhang X, Huang M, Asrar GR, and Leung LR. 2016. The Role of Climate Covariability on Crop Yields in the Conterminous United States. *Sci. Rep*. 6, 33160.

53. Lesk C, Rowhani P, and Ramankutty N. 2016. Influence of extreme weather disasters on global crop production. *Nature* 529, 84–87.

54. Liu S, Mo X, Lin Z, Xu Y, Ji J, Wen G, and Richey J. 2010. Crop yield responses to climate change in the Huang-Huai-Hai plain of China. *Agric Water Manage* 97:1195–1209.

55. Liu J, Goering CE, and Tian L. 2001. Neural network for setting target corn yields. *Trans. ASAE* 44(3): 705-713.

56. Lobell DB, and Field CB. 2007. Global scale climate–crop yield relationships and the impacts of recent warming. *Environ. Res. Lett*. 2, 014002.

57. Lobell DB, and Gourdji SM. 2012. The influence of climate change on global crop productivity. *Plant Physiol*. 160, 1686–1697.

58. Lobell DB, Roberts MJ, Schlenker W, Braun N, Little BB, Rejesus RM, and Hammer GL. 2014. Greater sensitivity to drought accompanies maize yield increase in the US Midwest. *Science* 344, 516–519.

59. Lobell DB, Schlenker W, and Costa-Roberts J. 2011a. Climate trends and global crop production since 1980. *Science* 333, 616–620.

60. Lobell DB, Bänziger M, Magorokosho C, and Vivek B. 2011b. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change* 1:42-45.

61. Mariano FL, Di Bella MC, Américo JD. 2015. Relationship between MODIS-NDVI data and wheat yield: A case study in Northern Buenos Aires province, Argentina. *Information Processing in Agriculture* 2, 73 – 8 4.

62. Masih I, Maskey S, Mussá FEF, and Trambauer P. 2014. A review of droughts on the African continent: a geospatial and long-term perspective. *Hydrol. Earth Syst. Sci*. 18, 3635–3649, 2014

63. MathWorks. 2005. Neural network toolbox. Natick, Mass. The MathWorks, Inc. Available at: www.mathworks.com/products/neuralnet/.

64. Mazdiyasni O, and Aghakouchak A. 2015. Substantial increase in concurrent droughts and heatwaves in the United States. *Proc. Natl. Acad. Sci*. USA 112, 11484–11489.

65. Milazzo A. 1986. Corn milling profile. *Assoc. Oper. Millers Tech. Bull*. 4651–4662.

66. Myers R. and Jayne TS. 2012. Multiple-Regime Spatial Price Transmission with an Application to Maize Markets in Southern Africa. *American Journal of Agricultural Economics* 94 (1): 174-188.

67. NCDC (National Climatic Data Center). 2011. Billion dollar U.S. weather/disasters. Asheville, NC: National Oceanic and Atmospheric Administration, National Climatic Data Center. http://www.ncdc.noaa.gov/oa/eports/billionz.html.

68. Noh HK, Zhang Q, and Han S. 2004. A neural network model of nitrogen stress assessment using a multispectral corn nitrogen deficiency sensor. ASAE Paper No. 041132. St. Joseph, Mich.: ASAE.

69. Nurhussen A. 2016. Application of NDVI in Vegetation Monitoring Using GIS and Remote Sensing in Northern Ethiopian Highlands. *Abyss. J. Sci. Technol*. Vol. 1, No. 1, 12-17.

70. Nuss ET, and Tanumihardjo SA. 2010. Maize: a paramount staple crop in the context of global nutrition. *Compr. Rev. Food Sci. Food Saf*. 9: 417–436.

71. Odhiambo LO, Yoder RE, Yoder DC, and Hines JW. 2001. Optimization of fuzzy evapotranspiration model through neural training with input-output examples. *Trans. ASAE* 44(6): 1625-1633.

72. Pannar 2012. Quality seed, know the maize plant. Pannar Seeds, Private Limited.

73. Parplies A, Dubovyk O, Tewes A, Mund J, Schellberg J. 2016. Phenomapping of rangelands in South Africa using time series of RapidEye data. *Int. J. Appl. Earth Obs. Geoinf*. 53, 90–102.

74. Piperno DR and Flannery KV. 2001. The earliest archaeological maize (Zea mays L.) from highland Mexico: new accelerator mass spectrometry dates and their implications. *Proc. Natl. Acad. Sci. U. S. A.* 98: 2101–2103.

75. Ranum P, Pena-Rosas JP, and Garcia-Casal MN. 2014. Global maize production, utilization, and consumption. *Ann. N.Y. Acad. Sci.* ISSN 0077-8923.

76. Ray JD, Gesch RW, Sinclair TR, and Allen LH. 2002. The effect of vapor pressure deficit on maize transpiration response to a drying soil. *Plant soil* 239, 113–121.

77. Riedmiller M, and Braun H. 1993. A direct adaptive method for faster backpropagation learning: The RPROP algorithm. Proceedings of the IEEE International Conference on Neural Networks (ICNN), pages 586-591. San Francisco.

78. Ritchie SW, Hanway JJ, and Benson GO. 1992. How a corn plant develops. Spec. Rep. 48 (rev.). Iowa State Univ. Coop. Ext Serv., Ames.

79. Rosegrant MW, Msangi S, Ringler C, Sulser TB, Zhu T, and Cline SA. 2008. International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model Description. International Food Policy Research Institute: Washington, D.C. http://www.ifpri.org/themes/impact/impactwater.pdf (accessed May 1, 2011)

80. Sanderson MG, Hemming DL, and Betts RA. 2011. Regional temperature and precipitation changes under high-end (≥4°C) global warming. Philosophical Transactions of the Royal Society - *A Mathematical, Physical & Engineering Sciences* 369:85-98.

81. Schlenker W, and Roberts MJ. 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proc. Natl. Acad. Sci. USA* 106, 15594–15598.

82. Schulze RE, Kiker GA, Kunz RP. 1993. Global climate change and agricultural productivity in southern Africa. *Glob Environ Chang* 3(4):330–349. https://doi.org/10.1016/0959-3780(93)90022-D

83. Sehgal VK, Jain S, Aggarwal PK, Jha S. 2011. Deriving Crop Phenology Metrics and Their Trends Using Times Series NOAA-AVHRR NDVI Data. *J. Indian Soc. Remote Sens*. 39, 373–381.

84. Severini AD, Borrás L, Westgate ME, Cirilo AG. 2011. Kernel number and kernel weight determination in dent and popcorn maize. *Field Crops Res*. 120, 360–369.

85. Shearer SA, Burks TF, Fulton JP, Higgins SF, Thomasson JA, Mueller TG. 2000. Yield prediction using a neural network classifier trained using soil landscape features and soil fertility data, in: Proceeding of Annual International Meeting, Midwest Express Center, Milwaukee, Wisconsin.

86. Shobha P and Rajib S. 2016. The Relationships between Climate Variability and Crop Yield in a Mountainous Environment: A Case Study in Lamjung District. *Nepal. Climate* 4, 13; doi:10.3390/cli4010013. www.mdpi.com/journal/climate.

87. Shock BM, Carpenter GA, Gopal S, and Woodcock CE. 2002. ARTMAP neural network classification of land use change. In Proc. World Congress of Computers in Agriculture and Natural Resources, 22-28. F. S. Zazueta and J. Xin, eds. ASAE Paper No. 701P0301. St. Joseph, Mich.: ASAE.

88. Siddique MRB, Hamid A, Islam MS. 2001. Drought stress effects on water relations of wheat. *Bot Bull Acad Sin* 41:35–39.

89. Sruthi S, Mohammed AMA. 2015. Agricultural Drought Analysis Using the NDVI and Land Surface Temperature Data; a Case Study of Raichur District. *Aquatic Procedia* 4, 1258 – 1264.

90. Sun J. 2000. Dynamic monitoring and yield estimation of crops by mainly using the remote sensing technique in China. Photogramm. *Eng. Remote Sens*. 66:645–650.

91. Tao FL, Yokozawa M, Xu YL, Hayashi Y, Zhang Z. 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agric Ecosyst Environ* 138:82–92.

92. Thornton PK, Jones PG, Ericksen PJ, Challinor AJ. 2011. Agriculture and food systems in sub-Saharan Africa in a four-plus degree world. *Phil Trans R Soc A* 369(1934):117–136. https://doi.org/10.1098/ rsta.2010.0246

93. Tucker CJ, Townsend JRG, and Goff TE. 1985. African landcover classification using satellite data. *Science*, 227, 369–375.

94. Ummenhofer CC, Hong Xu, Twine TE, Girvetz EH, McCarthy HR, Chhetri N, and Kimberly A. Nicholas KA. 2015. How Climate Change Affects Extremes in Maize and Wheat Yield in Two Cropping Regions. *American Meteorological Society*. Volume 28. 4653-4687.

95. UNEP GRID-Arendal (United Nations Environment Programme Global Resource Information Database- Arendal). 2009. From supply to food security. In The Environmental Food Crisis: The Environment's Role in Averting Future Food Crisis. A UNEP Rapid Response Assessment, eds. Nellemann C, MacDevette M, Manders T, Eickhout B, Svihus B, Prins AG, and Kaltenborn BP. 77-91. Norway: Birkeland Trykkeri AS. http://www.grida.no/publications/rr/food-crisis/ page/3571.aspx.

96. US CCSP (US Climate Change Science Program). 2008. The effects of climate change on agriculture, land resources, water resources, and biodiversity in the United States. A Report by the United States Climate Change Science Program and the Subcommittee on Global Change Research, eds. Backlund P, Janetos A, Schimel D, Hatfield J, Boote K, Fay P, Hahn L, Izaurralde C, Kimball BA, Mader T, Morgan J, Ort D, Polley W, Thomson A, Wolfe D, Ryan MG, Archer SR, Birdsey R, Dahm C, Heath L, Hicke J, Hollinger D, Huxman T, Okin G, Oren R, Randerson J, Schlesinger W, Lettenmaier D, Major D, Poff L, Running S, Hansen L, Inouye D, Kelly BP, Meyerson L, Peterson B, and Shaw R. Washington, DC: USDA. http://www.climatescience.gov/Library/sap/sap4-3/final-report/default.htm.

97. Verheye W. 2010. Growth and Production of Maize: Traditional Low-Input Cultivation. In: Land Use, Land Cover and Soil Sciences. Encyclopedia of Life Support Systems (EOLSS), UNESCO-EOLSS Publishers, Oxford, UK. Online available at: http://www.eolss.net. Accessed on October 28, 2014.

98. Vina A, Gitelson AA, Rundquist DC, Keydan G, Leavitt B, and Schepers J. 2004. Monitoring Maize (Zea mays L.) Phenology with Remote Sensing. *Agronomy Journal*, vol. 96.

99. Wang KJ. 2000. Studies on root physiological characteristics and their correlation with the aboveground parts of different yield potential maize (Zea mays L.) genotypes (in Chinese with English abstract). Shandong Agricultural University, PhD Dissertation.

100. World Health Organization and Food and Agriculture Organization of the United Nations (WHO/FAO). 2006. Guidelines on Food Fortification with Micronutrients. Allen L, B. de Benoist, Dary O, and Hurrell R, Eds. Geneva: World Health Organization.

101. Xiao GJ, Zhang Q, Yao YB, Zhao H, Wang YR, Bai HZ, Zhang FJ (2008) Impact of recent climatic change on the yield of winter wheat at low and high altitudes in semi-arid northwestern China. *Agric Ecosys Environ* 127:37–42.

102. Yang YZ, Feng ZM, Huang HQ, Lin MY. 2008. Climate-induced changes in crop water balance during 1960–2001 in Northwest China. *Agric Ecosyst Environ* 127:107–118

103. Yang CC, Prasher SO, Lacroix R, Sreekanth S, Patni NK, and Masse L. 1997. Artificial neural network model for subsurface-drained farmlands. *J. Irrig. and Drain. Eng*. 123(4): 285-292.

104. Zipper SC, Qiu J, and Kucharik CJ. Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. *Environ. Res. Lett*. 11, 094021 (2016).

Chapter 2

LITERATURE REVIEW

The literature review in this study is centred on the keywords: climate, phenology, drought and prediction as applied to maize production in this study. This section thus, presents a review of the application of climate, phenology, and drought to understanding their relationships with maize production and the application of the elements for maize yield prediction. Hence, literature on climate, phenology and drought research that are not applied to maize production are not considered in this review. It is anticipated that this chapter will be published in a peer-reviewed journal in the near future.

This chapter presents a review of the available literature and information on climate, phenology, droughts and application of artificial neural networks analysis to maize yield prediction. This chapter is intended to quantify the amount of work and to build a national perspective on the impact of the spatiotemporal variation of climate, phenology and drought on maize yield in South Africa. The data and information for this review are mainly collected from the peer-reviewed and published literature.

Climate change, phenology, drought and prediction studies on maize production in South Africa: A critical appraisal

***Omolola M. Adisa*[1,*]**, Joel O. Botai[1,2], Daniel Darkey[1], Abiodun M. Adeola[2,3], Abubeker Hassen[4], Christina M. Botai[2], Eyob Tesfamariam[5]

[1]Department of Geography, Geoinformatics & Meteorology, University of Pretoria, Private Bag X20, Hatfield 0028; lolaadisa@yahoo.com; daniel.darkey@up.ac.za

[2]South African Weather Service, Private Bag X097, Pretoria 0001; joel.botai@weathersa.co.za; abiodun.adeola@weathersa.co.za; christina.botai@weathersa.co.za

[3]School of Health Systems and Public Health, Faculty of Health Sciences, University of Pretoria

[4]Department of Animal and Wildlife Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; abubeker.hassen@up.ac.za

[5]Department of Plant and Soil Sciences, University of Pretoria, Private Bag X20, Hatfield 0028; eyob.tesfamariam@up.ac.za

* Corresponding author. lolaadisa@yahoo.com Tel.: +27 84 849 1170

This review has been submitted and under review with Journal of Agricultural Research. https://www.editorialmanager.com/agri/default.aspx

---

Abstract

Climate change threatens crop production and hence raises concerns for food security in regions of high vulnerability, among which is the sub-Saharan Africa region. The potential significant impact of climate change on food security has led to a rise in the studies that assess its impact, particularly on agriculture. To investigate this assertion, a systematic review of existing peer-reviewed papers that focus on the assessment of the impact of climate change and variability and the associated drought conditions on maize phenology and yield as well as maize yield prediction under changing climate has been conducted. This study used the ISI Web of Knowledge electronic database. The keywords used are [“climate change” or “phenology” or “drought”, or “prediction”] AND [“agriculture*” or “maize*”] AND [South Africa]. Articles were reviewed using the inclusion and exclusion criterion. A final total of 17, 5, 13 and 2 articles were reviewed for climate change, phenology, drought and prediction respectively. The articles were assessed according to the methodologies, which included process-based, statistical and mathematical as well as models. The results across the four components (climate change, phenology, drought and prediction) vary according to applied methods. The results suggest that process-based approach dominate the maize-climate change, phenology, drought and prediction studies. About 53% of studies on climate change are model based, while 25% of the studies on maize with phenology and drought themes are based on the use of statistical analysis. Maize yield prediction studies are generally lacking and the literature on the use of machine learning tools for maize yield studies over South Africa is generally subtle. A limitation commonly reported in the existing literature is the lack of sufficient climate observation data at appropriate temporal and spatial scale to support climate change study. Satellite-derived data offers a solution by providing data at the appropriate spatial and temporal scale.

2.0. Introduction

It is generally accepted that climate sensitive sectors such as agriculture, energy and water form an inextricable linkages (famously referred to the food-energy-water nexus) that ought to be understood from the “scholar-practitioner” viewpoint (a concept often advocated by the ecosystem services research, see for example Wasserman *et al.*, 2009) in order to ensure water and food security, and sustainable agriculture and energy production as articulated by the United Nations. Maize is one of the most important cereal crops for human and animal diets and therefore plays a vital role in global food security. It is not a surprise that climate impacts and adaptation strategies for maize production are increasingly becoming major areas of scientific interest. Admittedly, there has been a proliferation of scientific literature on the subject matter globally. Notwithstanding this scholarly enterprise, most reviews of the existing literature on maize production under changing climate has largely been focused elsewhere, yet, unacceptably subtle in Africa, a continent that is inadvertently threatened by food security and anaemic economies. This literature review focuses on the scholarly enterprise of maize production under changing the climate in South Africa. In particular, the review examines the central themes, approaches and key findings of the scholarly articles that delved on the impacts of climate change and variability and droughts on maize phenology and yield in South Africa.

Climate is defined as the average weather condition of an area over a long period of time, varies globally from decade to decade naturally. On the other hand, climate change is measured by evaluating the patterns of disparity in temperature, precipitation, humidity, wind, atmospheric pressure, atmospheric particle count as well as other meteorological variables in a particular region over long periods of time. Evident from numerous scientific studies have shown that there has been an increase in the level of greenhouse gases (GHG) in the atmosphere (IPCC 2018). This increase is associated to the rise in the level of emissions because of human economic activities (such as the burning of fossil fuels like oil, coal, natural gas and the clearing of forests), motivated by the demand for energy, goods and services. Global warming, in turn, has led to exceptional changes in the climate system, translating into more extreme and intense weather events, as well as greater climate variability (IPCC 2018). These changes are noticeable in the average global temperature increases (record shows that the past decade have been the hottest so far), global average sea level rise, average rainfall pattern changes (some regions experience dryness like southern Africa and the Sahel while some other regions like the northern part of Europe experienced higher rainfall), increased in the heavy rainfall occurrence and hash weather events across large land expanse, with more intense and prolong droughts conditions (DEA 2011).

Studies have shown that the African continent to be highly vulnerable to climate change, with greater vulnerability in the south of the Sahara (IPCC 2013; Christensen *et al.*, 2007). The vulnerability to climate is dependent on economic, social and political factors which are in most sub-Saharan Africa regions in poor situations (Cooper *et al.*, 2008). Additionally, Africa is vulnerable to climate change because of the existing burden of climate-related threats, such as the prevalence of infectious diseases (e.g. malaria) and food insecurity among others (Cooper *et al.*, 2008; Brown 2009). Further, Africa is vulnerable to climatic hazards, as a result of over reliance on agriculture, pastoralism, and fishing resources for their livelihood activities (Maddison *et al.,* 2006). For instance, it is projected that there will be an average increase in temperature of about 3-4 °C in Africa over the next century warming than the global annual mean (Boko *et al.*, 2007). Warming is projected all over the regions of the continent, however, the rate of change and magnitude varies considerably. A decreased amount in rainfall is projected for the southern part of Africa and its western boundaries, particularly during the winter harvest months (du Plessis *et al.,* 2017). In contrast, annual mean rainfall is projected to increase over East Africa, while there are uncertainties in projections for the Guinean Coast, Sahel and southern Sahara. In general, it is expected that there will be an increase in rainfall intensity and sporadic rain events such as floods and erosion across sub-Saharan Africa (Christensen *et al.,* 2007). More specifically as predicted by climate models, the mean air temperature over South Africa will increase by approximately 2 °C over the next century (Jury 2013). This expected increase is quite detrimental to plants and animals as these species are more vulnerable, although human is also affected by these both directly and indirectly.

Climate change impact on Agriculture has been acknowledged as a major area for research focus thanks to the marginal climatic conditions in many regions of sub-Saharan Africa, subsistence livelihoods, and constraint capacity for adaptation (Vogel and Reid 2005; IPCC, 2013). The prevalence of rain-fed agriculture in many of the sub-Saharan African regions leaves the Agricultural sector highly susceptible to rainfall variability (Cooper *et al.,* 2008). Furthermore, majority of Africa’s farmers including those in South Africa are small-scale farmers who are generally underdeveloped with few financial resources, limited access to infrastructure, and poor access to information (Pereira 2017). As a way of coping with climate change, many of the farmers rely on the existence of generations of indigenous knowledge in determining crop type to be planted and when to plant (Ziervogel *et al.,* 2014). Hence, as a coping mechanism, short growing crops such as maize, nuts, beans and melons are choice crops when limited rain is predicted (Rankoana 2016). Nevertheless, it is believed that extreme climate conditions will have an impact on their agricultural production (Mpandeli 2005; Midgley *et al.,* 2007). Therefore, in order to be able to substantiate the potential impact of climate change on Agriculture, with particular reference to maize crop, a literature review of existing body of knowledge is seen as the first step in providing a comprehensive and holistic insight to how climate change and variability and drought conditions affect maize yield across South Africa.

Therefore, the objective of this paper is to present a review of the available literature and information on climate and climate change, droughts with particular emphasis on the impacts on maize yield as well as the prediction of maize yield using an artificial neural network. This will help to typify and synthesize current knowledge on the problem, identify priorities for future research, and contribute to mitigation and adaptation initiatives. The important role that maize plays in South Africa as a staple food, as well as a major ingredient in animal feed, makes it indispensable.

2.1. Methods

A desktop systematic review of published peer-reviewed literature related to climate change, drought, phenology and prediction were conducted. A realist review approach developed by Pawson et al., 2005 was adopted. The methods build upon the methodology of the Cochrane systematic review, however, realist review seeks explanation, rather than empirical truth (Pawson et al., 2005). Defining keywords search was performed within the ISI Web of Knowledge electronic database. The "All fields" option was used. The keywords used are ["climate change" or "phenology" or "drought", or "prediction"] AND ["agriculture*" or "maize*"] AND [South Africa]. Articles not published in English were excluded. There was no restriction on the years of publication. This was done in order to gather information on past and current scientific publications. In general, only published articles, reviews, and conferences were reviewed. The reference list of the retrieved literature was assessed in detail to gain additional articles that might not have been picked up during the search. However, only literature with a direct link to maize were retained based on the inclusion and exclusion criteria. Table 1 summarizes the inclusion and exclusion criteria used for this review. The use of the inclusion and exclusion criteria resulted in a total of 17, 5, 13 and 2 articles for final reviews of climate change, phenology, drought and prediction respectively. For each reviews (i.e. climate change, phenology, drought and prediction + Maize) a table of guidelines was used. The tables indicate author(s) detail and year of publication, geographical location of study, dataset, methods and key findings.

Although an effort was made to conduct a detailed review, there might be more existing research work that would have been omitted either not having a direct word that has been used in the search or the works are not published. Approaches and models used to assess the vulnerability of maize production to climate change, drought, phenology and prediction were comprehensively reviewed and discussed. Table 1 shows the criterion used in the selection of publications included in the review and those excluded. Thus, the gaps in the existing knowledge are acknowledged and areas, where further research is required, are suggested in the review.

Table 2-1: Criterion for selecting publications reviewed

Included	Excluded
Available in ISI Web of Knowledge	Unpublished thesis or dissertations
All years	Qualitative analyses or reports
Publications in English only	Publications in languages other than English
Articles, conferences	reviews
Direct relationship/application for maize	Agricultural studies but not focused on maize
Studies conducted in South Africa only	Global and regional studies with no focus on South Africa
	Adaptation, awareness, without climatic or environmental data analysis

2.2. Results

2.2.1. A review of climate change and maize production in South Africa

Several studies have been carried out on the impact of climate change on maize yield/production in South Africa. This is in response to the projected high vulnerability of the region to climate change in order to assess and quantify the impact as well as to provide potential adaptation and mitigation measures and strategies. Table 2 provides a summary of the literature on climate change and maize production in South Africa. Table 2 indicates authors and year of publication, geographical location, dataset, methods and key findings.

The study by Schulze *et al.*, (1993) seems to be the pacesetter for the studies of climate change impact on maize in South Africa. The authors developed an analysis tool in order to simulate primary productivity and crop yields including maize for both present and the potential future climate conditions. They demarcated southern Africa into 712 relatively homogeneous climate zones, with each of them having specific climate, vegetation and soil response information. The study investigated the effects of increasing carbon dioxide concentrations and temperature. The results indicate that there was an increase in potential maize production with different intensity across geographic areas. As reported in Schulze et al., (1993) low crop yielding areas (that is, areas below 4 tonnes per hectare) increased with increase in carbon dioxide and temperature while they had less effect in high yielding areas (at least 8 tonnes per hectare). The study reported that there is a large dependence on crop yield and production on the intra-seasonal and inter-annual variation of rainfall.

Du Toit *et al.*, (2001), investigated the effects of El Nino-Southern Oscillation on maize production in South Africa. In order to simulate the production practices that will minimize the effect of El Nino, they compared simulations with results of yield trials at four sites using the CERES-Maize simulation model with seasonal weather predictions and El Nino analogue years. The simulated and experimental trials comprised of five planting dates, three cultivars and three-plant populations. They reported that the effect of El Niño on national maize yields ranges from near average (2100 kg ha^{-1} in 1976/77) to very low yields (875 kg ha^{-1} in 1991/92). They further indicated that the analogue year-technique is effective in determining the correct management options for predicted El Niño seasons. However, the authors concluded that the reliability of the results dependent on the correct selection of analogue years as well as the availability of quality climate data.

Table 2-2: Summary of literature reviewed on climate change and maize production in South Africa

Authors and year of publication	Dataset	Methods	Key findings
Schulze *et al.*, 1993	Climate, soil and vegetation response information	Agro-hydrological model and Geographic Information System	Production and crop yield largely depend on the intra-seasonal and inter-annual variation of rainfall
Du Toit et al., 2001		CERES-Maize crop simulation model	The effect of El Niño on national maize yields ranges from near average (2100 kg ha^{-1} in 1976/77) to very low yields (875 kg ha^{-1} in 1991/92).
Du Toit *et al.*, 2002		CERES-Maize crop simulation model	Maize yields are strongly affected by seasonal changes in precipitation.
Gbetibouo and Hassan, 2005	Topography, vegetation, temperature, rainfall and soil, socio-economic variables	Ricardian model	Production of field crops was sensitive to marginal changes in temperature as compared to changes in precipitation
Benhin, 2006	Farm household crop farming data, climate data, major soil types, runoff, and adaptation related variables like irrigation, livestock ownership, access to output markets and access to the public and other extension services	Ricardian model	Climate variables, especially for precipitation, have a non-linear relationship with crop net revenues in South Africa. vertisols and xerosols soil type may be harmful to crop farming and therefore aggravate the harmful effects of climate change, while others like acrisols and arenosols, may help reduce them. The runoff will also benefit crop farming, but harmful when in excess.
Walker and Schulze, 2006		CERES-Maize crop simulation model	The future climate scenarios of '2 × CO_2' and '2 × CO_2 + 10%rain' had the biggest positive effect on mean grain yield. And the biggest increase in losses of organic nitrogen was with the '2 × CO_2 + 2 °C' scenario where losses increased by up to 5%.
Abraha and Savage 2006	Daily and monthly total rainfall, daily and monthly minimum and maximum air temperatures, and solar radiant	CropSyst simulation model	Climate change scenario of increased carbon dioxide concentration, changes in mean air temperature influenced maize yields more than by precipitation
Benhin, 2008	Farm household surveys, long-term climate data, major soils and runoffs.	Ricardian model	Crop net revenues are expected to fall by as much as 90% by 2100 with small-scale farmers been most affected.
Walker and Schulze, 2008		Simulation	The western part of the Highveld is categorized by quite low mean annual precipitation (MAP); vastly variable yields, and while rainfall increases towards the east, inter-annual yield variability remains high

Authors and year of publication	Dataset	Methods	Key findings
Akpalu *et al.*, 2008	Precipitation, temperature, labor, fertilizer, seed, and irrigation	Generalized Maximum Entropy (GME) estimator and Maximum Entropy Leuven Estimator (MELE)	MELE fits the data better than the GME, also increased precipitation, increased temperature, and irrigation have a positive impact on yield.
Blignaut *et al.*, 2009	Rainfall	econometric model Simulation	The result indicate that between 1997 and 2006, the country has been about 2% warmer and 6% drier when compared to the 1970s. They further reported that for a 1% decrease in rainfall there is likely to be a 1.1% decrease in summer maize production and a 0.5% decrease in winter wheat
Gbetibouo *et al.*, 2010	Farm organization, Literacy rate, HIV prevalence, Farm income, % people below poverty, Farm holding, % Agriculture GDP, Farm assets, Access to credit, and Infrastructure index	Descriptive statistic/indicator approach	Regions most exposed to climate change and variability do not always correspond with those undergoing high sensitivity or low adaptive capacity. Additionally, vulnerability to climate change and variability is basically linked to social and economic development.
Moeletsi *et al.*, 2011	Rainfall	Descriptive statistic/indicator approach	Cessation of rains occurs early during the El Niño and later in La Niña years over most parts of the study area. As a result, leading to a longer than normal duration of the rainy season in La Niña years and shorter than normal duration in El Niño years. High maize production is recorded in La Niña years and reduction in production is associated with El Niño years.
Crespo *et al.*, 2011	Downscaled climate scenarios	AgroMetShell	The results indicate that water satisfaction index will increase by about 5% in eastern South African. The study lay the foundation to recommend efficient adaptation options to order to the negative impact expected in South Africa.
Moeletsi and Walker 2012	Daily rainfall data	Descriptive statistic/indicator approach	Onset progresses from east to west whereas seasonal rainfall and rainy season duration increases from west to east
Estes *et al.*, 2013	Downscaled climate scenarios	empirical and mechanistic modeling	The empirical modeling approach projected a reduction of about 3.6% in maize yield and about 10% reduction in the potential maize growing area.
Chiara *et al.*, 2014	Averaged daily rainfall	Generalised linear models	the models are able to reproduce a range of agriculture-relevant indices suitable for agricultural impact assessments

Du Toit *et al.,* (2002), assessed the vulnerability of maize production to climate change and adaptation in South Africa using the CERES-Maize simulation model. The result shows that maize yields are strongly affected by seasonal changes in precipitation. The results of their simulations indicated that some areas of the country for example in the marginal western part may become unsuitable for maize production, while regions in the eastern part may remain unchanged or experience increase in production under the current management practices.

In 2005, Gbetibouo and Hassan used Ricardian approach to measure the economic impact of climate change on major South African field crops (wheat, sugarcane, maize, soybean, groundnut, sunflower and sorghum) across 300 districts in South Africa. In their study, they analysed the future potential impact of additional climate change. By regressing the soil, farm net revenue on climate, as well as other socioeconomic variables they were able to capture the farmer-adaptive responses to climate variations. Their results specify that compared to precipitation changes, field crops production was more sensitive to marginal temperature changes. While the rise in temperature had a positive effect on the net revenue, rainfall reduction affected it negatively. Their findings also emphasized the importance of location and season when dealing with the change in climate, demonstrating the fact that there is the uneven spatial distribution of impact climate change and subsequently required adaptations across the different agro-ecological South African regions. Furthermore, the simulation results of climate change scenarios revealed numerous impacts that would prompt very distinctive shifts in farming patterns and practices in diverse regions. Among with are major shifts in growing seasons and crop calendars, interchanging between crops to the possibility of ample disappearance of some field crops from some region.

Similarly, Benhin (2006) used the revised Ricardian model to assess the economic impact of the predicted adverse climate changes on the country's crop farming and possible adaptation options. The data sets used by Benhin (2006) in his study included farm household crop farming, major soil type, districts runoff, long-term climate data, as well as adaptation information on variables like ownership livestock, irrigation, access to output market, public and other extension services from a number of districts in the country's nine Province. The result revealed that the effect of climate change on irrigated farms and dryland farms are different, the effect is not much felt by irrigated farms owing to the fact that it does not solely depend on rainwater. Also, small-scale farms feel the effect more than the large-scale farms, but this also depends on whether the farm is irrigated or rain-fed. He discovered that as advantageous as irrigation farming might be if not properly implemented it can aggravate the harmful effects of climate change. Furthermore, soil types like acrisols and arenosols reduce the harmful effect of climate change on crop production while others such as vertisols and xerosols are very harmful to crop farming. Temperature is disastrous to summer farming season but quite advantageous during the winter season. Benhin 2006 predicted 90% fall in crop net revenue by the year 2100, if proper adaptations measure is not put in place, most severely affected will be small-scale farmers.

Walker and Schulze in 2006 used the CERES-Maize crop model to assess the sustainability of smallholder rainfed maize production under different management and climate change scenarios for agro-ecosystems of Potshini village in KwaZulu-Natal. Their result revealed that the future climate scenarios of '2 × CO_2' and '2 × CO_2 + 10% rain' had the highest positive influence on mean maize yield. The scenarios lead to an increase of over 1000kg/ha of inorganic fertilizer and approximately 200 kg/ha with manure. The '+2 °C' climate change scenario had the major negative effects on maize yield and there was a very large loss of organic nitrogen of about 5% with the '2 × CO2 + 2 °C' scenario.

Abraha and Savage in 2006 investigated the potential impacts of climate change on the maize yield for the midlands of KwaZulu-Natal. They used ClimGen stochastic weather generator to generate the weather data comprising of daily and monthly total rainfall, daily and monthly minimum and maximum air temperatures, and solar radiant for the period 1971 to 2000 as an input into the CropSyst simulation model to simulate the potential of maize grain yield. They modified these weather data by plausible future climate changes under a normal planting date and dates 15 days earlier and 15 days later. According to Abraha and Savage (2006), there was no significant difference between the generated and observed weather data. From their findings, the simulated maize yield using the generated weather data had a significantly smaller variance than the simulated maize yield using the observed weather data. Additionally, Abraha and Savage (2006) reported that with climate change scenario of increased carbon dioxide concentration, changes in mean air temperature influenced maize yields more than by precipitation. They concluded that site specific analysis is more suitable for implementing mitigation measures as a result of the variations in maize planting date caused by climate change.

The study reported in Benhin (2008) assessed the economic impact of expected adverse climate change on South Africa crop farming. The Benhin's study used a revised Ricardian model and data acquired from long-term climate, major soils types, runoffs and farm household surveys. From the mean annual estimation, it was determined that a 1% increase in temperature will lead to an increase of about US$ 80.00 in the net crop revenue whereas a 1mm/month fall in precipitation leads to a fall of about US$ 2.00, with notable impacts in seasonal differences. Across the different farming systems, significant spatial differences were also noted. With selected climate scenarios, it was predicted that there will be up to 90% fall in the crop net revenues by the year 2100, to be felt mostly by the small-scale farmers. Benhin's study made recommendations to policymakers to fine-tune the policies and make them more focused on taking advantage of the relative benefits across seasons, spatially and farming systems, and thus making climate change beneficial instead of harmful.

Walker and Schulze (2008) extended their previous study conducted in 2006 over the western Highveld using the CERES-Maize model to simulate nine plausible climate change scenarios over a 44-year period. The results revealed that there is relatively low mean annual precipitation and high variability in maize yields in the western part of the Highveld while rainfall increases towards the east. Walker and Schulze (2008) further indicate that variability in yields increased with an increase in temperature in the moist part of the study area while inter-annual variability in yield remained unchanged in the drier part of the study area with a reduced mean yield of about 30% over 44 seasons. They concluded that the rate of soil organic nitrogen increased with a simulated increase in temperature and doubling of CO_2.

Furthermore, Akpalu *et al.*, (2008) used Maximum Entropy Leuven Estimator (MELE) and the Generalized Maximum Entropy (GME) estimator to investigate the impact of climate variability on maize yield in the Limpopo Basin of South Africa. Temperature and precipitation combined with traditional inputs variables like irrigation, seed, labor and fertilizer were used as proxies for climate variability. Akpalu *et al.,* (2008) discovered that the MELE has a better data fit than the GME. Additionally, they reported that increased temperature, precipitation and irrigation have a positive impact on maize yield. Further still, according to the results from the MELE the impact of climate variability on maize yield could probably be negative in case the change leads to increased temperature and reduction in precipitation at the same rate and vice versa. In addition, although irrigation had a positive impact on yield then its elasticity coefficient was lower than precipitation, which can be interpreted to mean that the impact precipitation has on yield can only be partially mitigated by irrigation.

Blignaut *et al.,* (2009) used a panel data econometric model to assess how changes in rainfall have been affecting maize and wheat production. According to Blignaut *et al.*, (2009), between 1997 and 2006, the country has been about 2% warmer and 6% drier when compared to the 1970s. In addition, Blignaut *et al.,* (2009) that a 1% decrease in rainfall would most likely result to a 1.1% decrease in summer maize production and a 0.5% decrease in winter wheat.

A study reported in Gbetibouo *et al.,* (2010) used descriptive statistics to develop a vulnerability index and compared vulnerability indicators across the nine provinces of the country in order to identify the most vulnerable farming areas in South Africa. They identified nineteen socio-economic and environmental indicators to reflect the three components of vulnerability: sensitivity, adaptive capacity and exposure. Their results revealed that the regions with the most exposure to climate change and variability do not always intersect with those experiencing high sensitivity or low adaptive capacity. Moreover, vulnerability to climate and variability is fundamentally connected with economic and social development. The Gauteng and Western Cape Provinces were found to be relatively low on the vulnerability index despite the fact that these provinces have high literacy rates, high levels of infrastructure development, and low shares of agriculture in total GDP. On the other hand, the highly vulnerable regions like KwaZulu-Natal, the Eastern Cape and Limpopo are characterized by high land degradation, densely populated rural areas, large numbers of small-scale farmers, and high dependency on rain-fed agriculture.

The implications of El Niño-Southern Oscillation (ENSO) on rainfall characteristics with reference to maize production in the Free State Province of South Africa was examined by Moeletsi *et al.*, (2011). The authors used rainfall data collected over 309 climate stations from 1950 to 2008 in Free State Province. The rainy season indices which include the onset of rains, cessation of rains, duration of the rainy season and seasonal rainfall total for each agricultural year were apportioned into El Niño and La Niña years. The results indicate no clear pattern for the onset of rains with some areas undergoing late onset and others early onset in both El Niño and La Niña years. The result further illustrated that the cessation of rains occurs early during the El Niño and later in La Niña years over most parts of the province. This eventually led to longer duration of the rainy season in La Niña years than the expected and shorter rains than normal duration in El Niño years. Also, a higher amount of cumulative rainfall is received in La Niña years while lower than normal rainfall is received in El Niño years seasonally. The author concluded that high maize production is recorded in La Niña years and reduction in production is associated with El Niño years.

Crespo *et al.,* (2011) used the AgroMetShell crop model to investigate the impact of various sowing decisions on the water satisfaction index and consequently on maize yield over southern Africa. They ran the AgroMetShell model for 176 stations under different climate change scenarios downscaled from 6 General Circulation Models. The simulation was performed for a 20 year control period (present climate) from 1979-1999 and a 20 year future period from 2046-2065. The change in water satisfaction index between the present period and future period was compared over southern Africa. The influence of sowing decision on yield variation was computed. The results indicate that water satisfaction index will increase by about 5% in eastern South African. They reported that the result can lay the foundation to dev recommend efficient adaptation options to order to the negative impact expected in South Africa.

Moeletsi and Walker in 2012 studied the characteristics of the rainy season in Free State Province of South Africa with reference to rain-fed maize production. Their study assessed rainy season duration, the onset of rains, cessation of rains and seasonal rainfall at various probability levels with daily rainfall data for 309 stations spanning from 1950 to 2008. They determined the onset of rains and cessation of rains using the 3 consecutive dekads (10-day periods) cumulative rainfall and 1 dekad cumulative rainfall respectively. Their findings revealed that over the Free State there was a large spatial variance for the onset of rains whereas there was a small variance for the cessation of rains. Also, onset progresses from east to west whereas seasonal rainfall and rainy season duration increase from west to east. Areas with low risk associated with rainy season characteristics highly suitable for maize production include eastern Motheo, the Fezile Dabi, the Thabo Mofutsanyane, eastern and northeastern Lejweleputswa districts. On the other hand, high-risk areas with low production include the southern and western parts of the Province.

In another study, conducted by Estes *et al.,* (2013), used the empirical and mechanistic modeling approaches to project climate impacts on South African maize and wheat production in 2055 using 18 downscaled climate scenarios. The study reported that the empirical modeling approach projected a reduction of about 3.6% in maize yield and about 10% reduction in the potential maize growing area.

In 2014, Chiara and others conducted a study to determine growing season characteristics from averaged daily rainfall data from nine stations in the northeastern region of South Africa (Chiara *et al.,* 2014). The generalised linear models were used for the study. The model was used to evaluate the relationship between local rainfall variability to large-scale climate drivers. The results indicated that the models were able to reproduce a range of agriculture-relevant indices suitable for agricultural impact assessments.

In summary, a total of 17 studies on climate change with a direct focus on maize in South Africa were reviewed using the inclusion and exclusion criteria to cut down from about 118 papers that we retrieved from the search. Studies based on the use of crop simulation models account for about 53% of the studies 9 out of 17 (CERES-Maize; 23%, Ricardian; 18%, CropSyst; 6%, and AgroMetShell; 6%). See figure 1. The remaining 47% are shared among studies that used descriptive statistical analysis, empirical and mechanistic model, generalized linear model, maximum entropy Leuven estimator and the generalized maximum entropy estimator. Many of the studies which include the dominant CERES-Maize were conducted between 2001 and 2008.

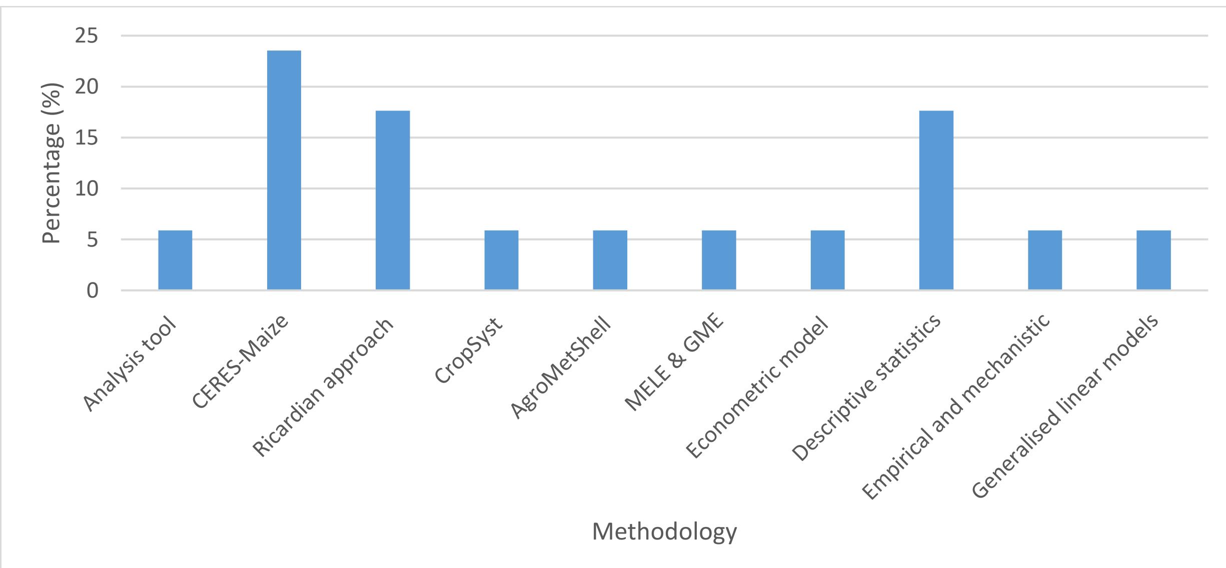

Figure 2-1: Percentage distribution of methodology used for climate change studies on maize production in South Africa

Additionally, it has been reported that the use of structural models such as the CERES-Maize model is associated with high cost such that it is difficult to implement the model in poor and developing countries, leading to such countries relying on experiments conducted in developed countries that share similar climatic characteristics (Mendelsohn, 2000; Adams, 1989). Although the Ricardian approach provides an advantage over the CERES-Maize model by providing farmers with adaptation options, the model requires a large number of input data which are only recently generated by the GEF/WB/CEEPA project (Dinar *et al.,* 2008) with restrictions on the accessibility of the data. The review shows that the customized crop simulation models CERES-Maize, Ricardian, CropSyst and AgroMetShell were conducted earlier while recent studies show new methodologies. Hence, the review shows a shift from the use of customized models to descriptive statistical analysis and machine learning tools such as the empirical and mechanistic model and the generalized linear models.

Further still, 59% of the studies on climate change and maize production in South Africa, used historical dataset, 23% used futuristic dataset while about 18% combined both dataset type for their analysis. Of which about 47% were model simulated, 24% were observed while the remaining 29% were both model simulated and observation dataset. Also, only 12% of the studies made recommendations to policymakers while the remaining 88% made no recommendation whatsoever. Another limitation identified in the reviewed studies is the fact that none of the authors identified any research gap for further studies.

Therefore, in overcoming the lack of adequate data at ideal temporal and spatial scale, Singles *et al.,* (2010) in their review, recommended that information derived from technologies such as remote sensing and genomics should be considered and integrated into future modelling efforts. Additional, as a result of the cost implications for using customized models, machine learning tools such as Artificial Neural Networks (ANN) proves to be adequate as an alternative.

2.2.2. A review of phenology and maize production in South Africa

Phenology studies the seasons and cycles of natural phenomena controlled by both climatic and environmental factors (Maignan *et al.,* 2008). It determines the duration and time taken by a plant canopy to be photosynthetically active and equally drives the annual uptake of carbon in an ecosystem (Jolly *et al.,* 2004; Cleland *et al.,* 2007). It also indicates long-term trends in climate as well as a short-term climatic variation as it is driven by precipitation, photoperiod and temperature (Hong *et al.,* 2014). Climate change occurs at both the global and regional level and it significantly affects vegetation dynamics through the increasing global mean temperature and change in the precipitation regimes (IPCC 2007). Consequently, climate change affects plant phenology due to its influence on the flowering time and the other plant developmental stages (Kang *et al.,* 2016). This section provides the review of existing studies on phenology as it relates to the understanding of the relationship between maize production and climate change in South Africa. The summary of the literature reviewed in this section is shown in Table 3 below.

Tadross *et al,* (2003) examined the inter-annual variability of the onset of the maize growing season over South Africa and Zimbabwe using rainfall data from Merged Analysis of Precipitation (CMAP) and the Computing Center for Water Research (CCWR). Tadross *et al.,* (2003) study aimed at determining and estimating variability in the onset of the maize growing season in order to enhance adequate measures for the planting of rain-fed maize. The results reveal that during the period of 1979-1997, the onset of the growing season tends to occur later in the season with the two data sets showing the same mean, standard deviation and trend estimates of onsets over South Africa particularly in the Limpopo valley and in the coastal areas. Tadross *et al.,* (2003) study further reveals that late or early onset of maize growing season is associated with the characteristics of rainfall over the subcontinent, indicating that increase in the frequency of intense rainfall over northeast Madagascar during the preceding August leads to early onset over Zimbabwe. Tadross *et al.,* (2003) concluded that onset variability is partially forced by synoptic conditions, and the use of general circulation models successfully depends on their simulation of the regionally irregular component of the westerly circulation to approximate onset.

Fanadzo *et al.,* (2009) investigated the agronomic factors constraining maize grain productivity at the Zanyokwe irrigation scheme (ZIS), Eastern Cape, South Africa. The purpose of Fanadzo *et al.,* (2009) study was focused on two main target, the first experiment comprise an evaluation of the relationship between cultivar (PAN6777 and DKC61-25), planting time (early: within the first 28 days of beginning of season on 15 November or late: planting after 15 December), nitrogen (N) rate (60 and 250 kg N ha^{-1}), and planting population (40 000 and 90 000 plants ha^{-1}) on maize grain yield, and the second experiment compared the grain yields of new hybrids to commonly grown cultivars by farmers (they compared eight cultivars; of which two were popularly grown by ZIS farmers from the three maturity classes (early, medium and late)) from 2002 to 2004. When maize was planted early and fertilized at 250 kg N ha^{-1} higher yields were obtained notwithstanding of the cultivar. With an early growth at 90 000 plants ha^{-1} the short-season cultivar DKC61-25 had an optimal yield, at the same time PAN777 the long-season cultivar had better performance at 40 000 plants ha^{-1}. In general, planting time and N rate influences yield the most. Also from their findings, they concluded that the lack of viability of smallholder irrigation schemes in South Africa is resultantly linked to the unsuitable agronomic practices for irrigated crop production via farmers.

Fanadzo *et al.,* (2009) recommended that more focused research targeted at addressing the problems of fertility, cultivar selection, planting time, and population management in ZIS.

Vrieling *et al.,* in 2013 calculated the length of growing period (LGP), its variability and trends using 30 years NDVI time series (that is GIMMS NDVI3g from 1981-2011) over Africa. Vrieling *et al.,* (2013) employed a variable threshold method alongside with a searching algorithm to determine start-and end-of-season, from which a reliable estimate of LGP was obtained for sub-humid, semi-arid and arid climates dependable through time and space. In semi-arid and arid high LGP variability was dominant, and this poses threat to crop production. Furthermore, from Vrieling *et al.,* (2013) findings for parts of Tanzania, northern Mozambique and for the northern part of the Sahel there were significant negative trends, as well as in the short rains of eastern Kenya. Further still, in eastern Kenya, across western Africa and in southern Africa there were positive long rains trends. Vrieling *et al.,* (2013) study provides useful information for farming systems mapping and an avenue for the effective study of climate variability and other drivers of change on crop suitability and vegetation.

Akinnuoye-Adelabu and Modi in 2017 carried out a study on the influence of planting dates and harvesting stages on maize yield under rain-fed conditions, conducted on the research farm Pietermaritzburg at the University of KwaZulu-Natal, South Africa between 2014/15 and 2015/16. The planting dates consist of early (November), mid (December) and late planting dates (January), meanwhile, harvesting takes place at milk stage, dent stage and physiological maturity. From their findings variables of yield parameters and plant physiological growth is the major determinant of maize response to planting and harvesting stages. 2015/16 been a drier season experienced more obvious significant differences in physiological parameters and growth compared to the 2014/15 season. At both seasons, early and mid-planting had a positive influence on measured parameters. Nevertheless, more favourable to maize growth and yield during the drier season was the mid planting date. The relationship between the harvesting stages and planting dates did influence grain yield, ear length, thousand seed weight and diameter significantly. Owning to the increment in the variability of climate, maize planted lately are on high risk of having lower yield regardless of its planting dates and there is a high probability of it not attaining the stage of physiological maturity. There was substantially high yield when maize was harvested at dent stage under early and mid-planting dates.

Moeletsi in 2017 mapped the maize growing period over the Free State Province of South Africa: Heat Units Approach. He used the thermal index concept to determine the length of the growing season of the short season, medium season and the medium-late season varieties of maize crop for different planting dates (1st dekad of October to 1st dekad of January). Moeletsi's results revealed high spatiotemporal variation in the median growing period for all three maize varieties. Moeletsi (2017) also discovered that there is a relatively short length of the growing period during October to early December for all three maize varieties having values less than 100,120 and 120 respectively in some areas. Furthermore, in most of Free State, the duration of the sowing period increases exponentially from the 2nd dekad of November to 2nd dekad of December, depending on the crop variety and region. Moeletsi (2017) findings also show that long growing period is likely to align maize growing period with water shortages as well as dates of high frost risk. Therefore, to produce maize crop that grows and develop well, it is important to take into consideration the thermal time requirements of the cultivar in choosing the suitable planting date.

Table 2-3: Summary of literature reviewed on phenology and maize production in South Africa

Authors and year of publication	**Dataset**	**Methods**	**Key findings**
Tadross *et al.*, 2003	Rainfall	Descriptive statistical analysis	The results reveal that during the period of 1979-1997, the onset of the growing season tends to occur later in the season with the two data sets showing the same statistical characteristics. Also late or early onset of maize growing season is associated with the characteristics of rainfall over the subcontinent
Fanadzo and Chiduza 2009	Maize cultivars (PAN6777 and DKC61-25), and maize grain yield	Two on-farm trials	When maize was planted early and fertilized at 250 kg Nha-1 higher yields were obtained notwithstanding of the cultivar.
Vrieling *et al.*, 2013	GIMMS NDVI3g	Threshold method combined with a searching algorithm	In semi-arid and arid high LGP variability was dominant, and this poses threat to crop production.
Akinnuoye-Adelabu and Modi 2017	Rainfall	Field trials	Variables of yield parameters and plant physiological growth are the major determinant of maize response to planting and harvesting stages.
Moeletsi 2017	Temperature data	Heat Units Approach	High spatiotemporal variation in the median growing period for all three maize varieties.

In summary, out of the 25 papers review, only a total of 5 studies was found to have a direct link to phenology and maize conducted in South Africa. Furthermore, 4 out of the 5 studies relied on the use of climatic data (rainfall and temperature) (Table 3). The availability of climatic datasets for a long period of time and over a large area has been reported as a limitation for these studies and hence, the studies were conducted over a small geographical landscape. With high climate variability in South Africa, (Kruger and Nxumalo, 2017), the transference of these studies to another region might be difficult. Many of the studies involve field trials which are cumbersome and expensive to perform. Remote sensing technology such as employed by Vrieling *et al.*, (2013) provides alternatives to monitor changes in vegetation phenology induced by a climate with less cost implication and over a large spatial and temporal scale (Hong *et al.*, 2014).

2.2.3. A review of droughts and maize production in South Africa

Drought is considered as a slow and creeping recurring natural phenomenon (Wilhite 2000), one of the most complex and damaging natural disaster, with its impacts cutting across different sectors of the economy, for example, agriculture, water, tourism, transport, energy, and ecosystem) (Yang *et al.,* 2015). In particular, most rain-fed regions across the world suffer from drought-induced crop failure and water shortage problems (Grayson 2013; Zhang & Zhang 2016). In Africa, rain-fed agriculture is viewed to be the most vulnerable sector to drought and its inherent impacts due to the aridity conditions (Wilhite 1992). Drought conditions in South Africa, particularly, has crippled major economic sectors, e.g. water resources and agriculture in and across different provinces (Botai *et al.,* 2016; Botai *et al.,* 2017). This section reports the overview of studies done in South Africa that relate to drought and maize production. Table 4 gives the summary of the reviewed studies.

Al du Pisani (1987) used the CERES-MAIZE model as a potential tool for evaluating the effects of drought on the early stage of maize growing. Observed weather data of temperature and rainfall combined with median data was used to develop the model for predicting maize yield in response to drought conditions. The model was validated using yield data from various locations of different annual rainfall amount. The model was also evaluated for its sensitivity to planting dates and soil water parameters. The results of the model indicated a strong correlation between yield predictions using observed weather data combined with median data and a strong correlation between yield predictions using only observed weather data.

Table 2-4: Summary of literature reviewed on drought and maize production in South Africa

Authors and year of publication	Dataset	Methods	Key findings
Al du Pisani 1987	Maize yield, rainfall, temperature and median data	CERES-MAIZE model	The results of the model indicated a strong correlation between yield predictions using observed weather data combined with median data and a strong correlation between yield predictions using only observed weather data.
Steynberg *et al.*, 1989	Maize yield, fertilizer	pot experiment	Maize yield response to drought stress. Variation in sensitivity was more evident in plants with deficient in the nutrient
De Jager *et al.*, 1998	Southern oscillation index	Spatial analysis (GIS)	Maize yield forecasts, probabilities of non-exceedance and the demarcation of drought severity areas.
Dube and Jury 2000	Rainfall, temperature and NDVI	Statistical analysis	Drought in the study area have a 3 to 5-year cycle, the frequency and intensity of the drought have increased over the last three decades, extreme climatic events such as drought and floods account for about 50% of crop failure in KwaZulu-Natal and nearly 60% for the entire country.
Mabhaudhi and Modi 2010	Landrace and hybrids maize	Standard germination test and electrical conductivity	Landraces may possibly have the similar viability as hybrids and a better tolerance to stress during early establishment of the crop
Moeletsi *et al.*, 2012	Rainfall, temperature, maize	Water Requirement Satisfaction Index (WRSI)	Seasonal rainfall and the WRSI showed high interseasonal variability, while seasonal maize water requirements showed low variability
Moeletsi *et al.*, 2013	climate and weather forecasts		Prediction of drought index at different planting dates, and the onset of rains using climate and weather forecasts.
Masupha *et al.*, 2015	Daily rainfall	Statistical analysis	High probabilities of short dry spells regardless of the planting time across the study area. High risk of yield reduction was associated with plating after the first onset of rains, while it is less with planting after second and third onsets of rains. The best appropriate time for farmers to plant is between mid-November to mid-December in order to minimize the risk of yield loss and or reduction
Mazvimbakupa *et al.*, 2015	Landrace and hybrids maize	Standard germination, electrical conductivity, and tetrazolium tests	The study reported that landrace GQ2 performed similar to the hybrids, however, hybrids had a superior quality of seed compared to the landraces. Yield came out poorly under the controlled conditions for the two maize type.
Masupha and Moeletsi 2017	Climate data	Standardized precipitation evapotranspiration index	There was at least one drought occurrence in every two growing seasons, there was no significant trends over the catchment but detected 1991/92 as the most extreme drought period over the period of study. The result further indicated that in the region of high and moderate rainfall, December is not ideal for the planting of a 120-day maturing maize as a result of extreme drought associated to the month and which coincides with the flowering to

Authors and year of publication	Dataset	Methods	Key findings
			the grain-filling stage, while planting in October should be avoided in regions of low rainfall.
Masupha and Moeletsi 2018	Precipitation, Potential Evapotranspiration (PET), soil	Water Requirement Satisfaction Index (WRSI), Standardized Precipitation Evapotranspiration Index (SPEI)	The study area experiences mild to moderate droughts, conditions are predicted to change to significantly drier conditions.
Robert *et al.*, 2018		CropSyst crop model	The modified version of the CropSyst model predicted an increase of about 30% for maize yield and showed a higher variability than the existing CropSyst version when forced with climate change projection scenarios, in addition to this there is an expected increase in drought severity and temperature increase at the horizons 2030 and 2050 whereby leading to decrease in maize yield.
Robert *et al.*, 2018	Maize cultivars	Experimental plot	Irrespective of the cultivar the effect of drought on grain yield was more noticeable beginning from the mid-vegetative to tasseling stages, the effect of flooding was more obvious for both cultivars at the early vegetative stage causing yield reductions.

Steynbery *et al.,* in 1989 conducted a study on the sensitivity of maize to drought in relation to soil fertility and water stress at various growth stages. To determine drought sensitivity at differential soil fertilities, they grew the maize under controlled conditions in a pot experiment (four water stress treatments were applied). Steynbery *et al.,* (1989) obtained soil from a fertilization trial field where soil fertility difference had been developed for about 45 years. The results indicate that maize yield response to stress as a result of the drought. Furthermore, maize deficient in Potassium, Nitrogen and Phosphorus seemingly had less tolerant to water stress conditions compared to the well fertilized plants. Agreeing with expectations, during the reproductive phase, plants were more drought sensitive than during the vegetative stage. Nevertheless, the variation in sensitivity was much more evident in plants with deficient in the nutrient. Steynbery *et al.,* (1989) concluded that potassium, nitrogen and phosphorus played a crucial role in drought adaptation mechanisms for well-fertilized plants.

De Jager *et al.,* in 1998 developed a framework for forecasting the extent and severity of drought on maize in the Free State province of South Africa. Using the phase of the southern oscillation index, the system is able to map and qualify drought hazard in maize by running a maize crop growth models in GIS (geographic information system). The study area was mapped into 9800 homogeneous natural resource zones. Maize yield forecasts were computed and were compared with long-term cumulative probability distribution functions of yield. Hence, probabilities of non-exceedance of calculated and the demarcation of drought severity areas were done. Although the system is widely accepted and being used, the accuracy of the forecasted yield has not been performed.

Dube and Jury in 2000 used long-term rainfall, temperature and satellite derived vegetation indices; the normalized difference vegetation index (NDVI) data to investigate climate variability over KwaZulu-Natal for about three decades. The results indicate that drought in the study area has a 3 to 5-year cycle. Additionally, it is reported that the frequency and intensity of the drought have increased over the last three decades. The result further indicates that extreme climatic events such as drought and floods account for about 50% of crop failure in KwaZulu-Natal and nearly 60% for the entire country.

In 2010, Mabhaudhi and Modi explored the performance of local and hybrid maize at an early stage under two water stress regimes. The goal of the study was to make a comparison between two local landraces (white (Land A) and dark red (Land B)) selections of maize and two hybrids (SC701 and SR52) prevalent among the KwaZulu-Natal small-scale farmers, in order to determine water stress tolerance and seed performance during seedling establishment. Mabhaudhi and Modi (2010) used electrical conductivity and standard germination test to assess the quality of seed under laboratory conditions. Mabhaudhi and Modi (2010) used pine bark at 25% and 75% field capacity (FC), respectively for a period of 21 days to perform seedling emergence in seedling trays. From their findings, all the seed types indicated high germination capability (>93%) with highly significant differences in all the varieties. Furthermore, Mabhaudhi and Modi (2010) discovered that in the two water stress regimes the hybrids varieties developed faster than the landrace varieties whereas the landraces did perform better than hybrids under stress situations. Mabhaudhi and Modi (2010) concluded their study indicating that there is the likelihood that landrace has similar viability as hybrids and a better tolerance to stress in the early stage of crop establishment.

Moeletsi *et al.,* (2012) used the Water Requirement Satisfaction Index (WRSI) at three different probability levels to quantify drought affecting rain-fed maize production in the Free State based on climate data from 227 weather stations. Results showed high spatial variability in the suitability of different areas: the southern and southwestern localities are unsuitable due to high drought incidences; the northern, central, and western regions are marginally suitable; the eastern, northern-eastern areas and a few patches in the northwest are highly suitable with relatively low drought severity. Moeletsi *et al.,* (2012) indicated that proper choice of maize varieties to suit conditions at different localities is crucial. The Mann–Kendall test and coefficient of variation were further used to determine trends and temporal variability, respectively, in the WRSI, seasonal rainfall, and seasonal maize water requirements. Results of this analysis revealed no significant positive trends in the WRSI, no significant negative trends in seasonal rainfall, and no significant positive trends in maize water requirements, contradicting previous findings of increased drought severity. Seasonal rainfall and the WRSI showed high inter-seasonal variability, while seasonal maize water requirements showed low variability. In view of these observations, it is apparent that the realignment of management practices is an overdue prerequisite for sustainable maize production.

Moeletsi *et al.,* (2013) developed an agro-climatological risk tool for dryland maize production in the Free State Province of South Africa. The decision support tool comprises two major parts namely forecasting and climatological risk. The user is able to obtain drought stress risk for 100-

day, 120-day and 140-day maize cultivars for planting windows beginning from October-January using the climatological risk component. Furtherly, the tool is capable of determining the best suitable planting dates based on the risk related to the climatology onset and cessation of both frost and rains. With the use of climate forecasts acquired from the national forecasting centers, drought index can be predicted at different planting dates providing valuable information for farmers required for planning towards the next season. The tool is equally capable of predicting the onset of rains using climate and weather forecasts.

Masupha *et al.*, (2015) investigated the occurrence of a dry spell in relation to maize growing season in the Luvuvhu River Catchment. Dry spells were categorized into three, namely, short, medium and long dry spells using daily rainfall data from 1945–2014 over 12 stations. Using the Spearman's rank correlation test to perform trend analysis on the frequency of dry spells per growing period the results indicated that, all the stations exhibit high probabilities of short dry spells regardless of the planting time. The result further indicates that the high risk of yield reduction was associated with planting after the first onset of rains, while it is less with plating after second and third onsets of rains. Masupha *et al.,* (2015) concluded that it will be appropriate for farmers to plant between mid-November to mid-December in order to minimize the risk of yield loss and or reduction.

Mazvimbakupa *et al.,* (2015) conducted a study on the quality of seed and water use characteristics of maize landrace in comparison with some selected commercial hybrids. The purpose of their study was to evaluate seed quality alongside water use characteristics of two commercial hybrids (SC701 and PAN53) compared with two maize landraces (GQ1 and GQ2). Mazvimbakupa et al., (2015) used the tetrazolium, standard germination and electrical conductivity test to determine the quality of the seed in a controlled environment. The study reported that landrace GQ2 performed similar to the hybrids, however, hybrids had a superior quality of seed compared to the landraces. Mazvimbakupa *et al.*, (2015) also discovered that yield came out poorly under the controlled conditions for the two-maize type.

Masupha and Moeletsi in 2017 used climatic data from 7 weather stations from 1975 to 2014 to derive Standardized Precipitation Evapotranspiration Index (SPEI) in order to investigate drought frequency and severity analysis during the growing period of maize in the Luvuvhu River catchment area. Temporal variation of droughts was computed, and the Spearman's Rank

Correlation test was used to determine trends. The results indicate that there was at least one drought occurrence in every two growing seasons. Masupha and Moeletsi (2017) reported that there were no significant trends over the catchment but detected 1991/92 as the most extreme drought period over the period of study. The result further indicated that in the region of high and moderate rainfall, December is not ideal for the planting of a 120-day maturing maize as a result of extreme drought associated to the month and which coincides with the flowering to the grain-filling stage, while planting in October should be avoided in regions of low rainfall.

Masupha and Moeletsi in 2017 analyzed the potential future droughts limiting maize production, in the Luvuvhu River catchment area of South Africa. They calculated the Water Requirement Satisfaction Index (WRSI) and the Standardized Precipitation Evapotranspiration Index (SPEI) in order to assess drought on a 120-day maturing maize crop spanning from 1980/81 to 2089/90. SPEI revealed that 40-54% of the agricultural seasons throughout the base period experienced mild drought conditions (SPEI 0 to -0.99), corresponding to a cessation of once in two seasons. Conversely, the results from WRSI evidently showed that station in the drier regions (that is areas with annual rainfall < 600 mm) of the catchment experienced mild drought (WRSI 70 -79) conforming to adequate crop performance every season. Masupha and Moeletsi (2017) result further revealed an overall mild to moderate droughts in the commencement of the near-future climate period (2020/21 to 2036/37) with SPEI values not diminishing below -1.5. However, the far-future climate period (2055/56 -2089/90) conditions are predicted to change to significantly drier conditions. Masupha and Moeletsi (2017) study made available information for farmers in the area as to how they can adequately prepare for the future agricultural season, and equally implement drought reduction strategies.

Robert *et al.,* (2018), modelled the impacts of extreme heat and drought on maize yield using an existing and modified version of CropSyst crop model. Robert *et al.,* (2018) study was conducted over an experimental station where the models were calibrated and validated by using field data collected from 2004 to 2008. The results indicated a significant difference between the two versions of the model during extreme drought and heat events. The modified version of the CropSyst model predicted an increase of about 30% for maize yield and showed a higher variability than the existing CropSyst version when forced with climate change projection scenarios, in addition to this there is an expected increase in drought severity and temperature increase at the horizons 2030 and 2050 whereby leading to decrease in maize yield.

Robert *et al.,* (2018), examined the response of maize yield to extreme events such as droughts and floods. The study compared the growth, development, yield, yield components, and physiological responses of drought-tolerant PAN 413 and drought intolerant PAN 6Q-245 maize cultivars for a period of two years under flooding and drought conditions. Robert *et al.,* (2018) reported that irrespective of the cultivar the effect of drought on grain yield was more noticeable beginning from the mid-vegetative to tasseling stages, with a difference of about 53-58% in the 2015/2016 season and 34-42% in the 2016/2017 season from the control. In case of flooding for both cultivars, the effect was more obvious at the early vegetative stage having yield reductions oscillating between 26-30% in the 2015/2016 season and 15-21% in the 2016/2017 season. Robert *et al.,* (2018) results also revealed that the two cultivars are susceptible to possible flooding events before the tasseling stage. Robert *et al.,* (2018) recommended the development of maize cultivars by plant breeders that can tolerate numerous stress.

In summary, the review indicates that although many studies have been undertaken in South Africa in response to drought occurrence, only a few of these studies have investigated the impacts of drought on maize. A total of 103 peer-reviewed published works on drought were reviewed. However, only 13 have direct application to maize production. Additionally, from the results of the review, the first set of published works were in 1987 and 1989. No other published work was picked up during the search until 1998 and 2000. With a number of studies on drought after the major drought periods of 1991/92, 1994/95, 2002/03 and subsequently leading to a spike in research, there was no significant number of researches on drought relating to maize production until 2010. The increase in drought-maize research is perceived to be due to increase frequency and evidence of the impact of drought on Agriculture and maize being a major staple food in the country. A total of 6 publications between 2015 till date; 2018 accounts for 46% of the total publication on drought-maize research; 2015(2), 2017(1) and 2018(3). Furthermore, while a few of the studies have adopted the use of existing crop models(2), others have explored drought indices such as the SPEI(2) and WRSI(2), geospatial technology(1) and other statistical approaches in providing solutions for a sustainable maize production under a climate change-induced drought conditions. Majority of the studies are field experimental based and conducted over a small area with the maize growing provinces, only 1 of the studies had considered data from several locations across the maize growing province. Hence, studies considering the overview of drought conditions and its impacts across the major maize growing provinces are lacking. The frequency, intensity and duration of drought vary over South Africa (Rouault & Richard 2003) indicating that different mitigation and adaptation measures will be required. Therefore, studies on the impact of drought on maize yield across the maize producing regions of South Africa is imperative for adequate decision making towards sustainable food production and security.

2.2.4. A review of artificial neural networks application to maize production in South Africa

Maize yield prediction offers a platform for assessing, monitoring the performance of sown seeds. It also estimates its yields in response to all environmental and biological factors which includes farm management practices. The review of maize prediction in South Africa indicated that numerous crops yield estimated studies have been carried out using different approaches. For instance, Malherbe *et al.,* (2014), used the seasonal forecasts of the SINTEX-F coupled model estimate maize yield and streamflow over north-eastern South Africa. Downscaled forecast for austral summer with a 1-month lead from a Global Coupled Model over a period of 28 years was used. The model serves as a starting point study for the development of a robust climate and environmental based model for estimating maize yield potential.

Ngie and Ahmed in 2018 attempted to estimate maize yield using multispectral satellite data sets (SPOT 5) and the random forest algorithm. In their study, they used canopy reflectance acquired from a multispectral sensor to develop vegetation indices which served as input variables into an empirical pre-harvest maize yield prediction model in the northeastern section of Free State province, South Africa. Monitoring some fields in this region where maize is grown under rain-fed conditions they were able to measure the grain harvested after 7-8 months. Prior to the grains harvested in July of 2014 a suitable medium resolution SPOT 5 images over the area was acquired in March and June, to estimate maize grain yields using the random forest algorithm predictive models and the March images. According to Ngie and Ahmed (2018) results from the two selected field, the regression analysis shows a good accuracy of high coefficient of determination values, low mean bias error and root mean squared error of prediction values for both fields. However, Ngie and Ahmed (2018) study's limitation is that it is site-specific that is it does not cover the whole of South Africa. The use of remote sensing in this study offers the possibility of extending such work using phenological characteristics of maize growing fields.

With just few studies on maize yield prediction, no study in South Africa has reported the use of the robust yet inexpensive advantage of machine learning systems such as the artificial neural network (ANN). In ensuring that farmers particularly the rain-fed agricultural farmers adapts to climate change and avoid yield loss, there is a need for the development of a system that can be operationalized, easy to use and at a very cost-effective rate. The necessity for an intelligent system that can adequately predict crop yield has made ANN become a technology which offers a solution for the multifaceted problems in agricultural researches, particularly in the face of climate change (Alvarez 2009; Aditya *et al.*, 2016). ANN can solve many complex problems that cannot be resolved by a linear system (Khairunniza-Bejo *et al.,* 2014; Matsumura *et al.,* 2015). Additionally, machine learning tools such as the ANN is a vital tool particularly for innovating and developing improved products for climate change vulnerable society (Khairunniza-Bejo *et al.,* 2014).

2.3. Conclusion

Studies on maize production relating to climate change, drought, phenology and prediction in South Africa are reviewed. The inclusion and exclusion criteria were used after searching through the ISI web of knowledge electronic database. All the articles reviewed suggest evidence of the negative impact of climate change and its associated derivatives such as drought on maize production. The review indicated a principal use of existing crop models such as CERES-Maize, AquaCrop, CropSyst, AgroMetShell and Ricardian models. The models are not locally designed but are customized and validated in most cases for their application over South Africa.

Although, many of the reviewed literature has studied the relationship between maize yield and climatic variables, issues such as the inadequate input data at appropriate time and scale is a commonly reported limitation to many of the studies. In addition, the review of existing studies on climate-related studies on maize production indicated that only a few of the study has considered the influence of other agro-climatic variables such as such as potential evapotranspiration and soil moisture on maize. Furthermore, none of the existing studies has given a comparison of the effect of climate, phenology and drought over the major maize producing province of South Africa as many of the current studies were conducted over a small area of specific maize producing provinces. Consequently, there is no existing work indicating the principal climatic elements influencing maize production and to what degree across the maize producing areas.

Studies have shown that the use of satellite derived data has the advantage of providing adequate data at ideal spatial and temporal resolutions for studies such as this. Climatic variables such as rainfall, temperature and agro-meteorological variables such as potential evapotranspiration, soil moisture, NDVI can be derived from satellite data (Lee et al., 2010). This review reveals that despite the evident impact of climate change and other derivatives on maize production, there is no operationalized maize yield predicting system. The development of a predicting system is imperative to ensure food security for South Africa and mitigate its impact small-scale farmers and the rain-fed production system.

Acknowledgment

I will like to acknowledge the University of Pretoria through the Animal change project and DST for providing bursary through a grant that was received by the University of Pretoria.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Abraha, M.G., Savage, M.J. (2006) Potential impacts of climate change on the grain yield of maize for the midlands of KwaZulu-Natal, South Africa, Agriculture, *Ecosystems & Environment* 115, 150-160. DOI: 10.1016/j.agee.2005.12.020.

2. Adams, R.M. (1989). Global climate change and agriculture: An economic perspective. *American Journal of Agricultural Economics* 71, 1272-1279.

3. Aditya, K.S., Sanjay, H.A., Deshmukh, A. (2016) A parameter based customized artificial neural network model for crop yield prediction. *Journal of Artificial Intelligence 9, 23-32.*

4. Akinnuoye-Adelabu, D.B., & Modi, A.T. (2017) Planting Dates and Harvesting Stages Influence on Maize Yield under Rain-Fed Conditions. *Journal of Agricultural Science* 9, No. 9; 2017 ISSN 1916-9752 E-ISSN 1916-9760, Canadian Center of Science and Education.

5. Akpalu, W., Ringler, C., Hassan, R. (2008) Climate variability and maize yield in South Africa: Technical Report. https://www.researchgate.net/publication/46442193.

6. Al du Pisani (1987). The CERES-MAIZE model as a potential tool for drought assessment in South Africa. ISSN 0378-4738 = Water SA Vol. 13. No. 3.

7. Alvarez, R. (2009) Predicting average regional yield and production of wheat in the Argentine Pampas by an artificial neural network approach, *European Journal of Agronomy* 30, 70-77.

8. Benhin, J.K.A. (2006) Climate change and South African agriculture: Impact and adaptation options. CEEPA Discussion Paper #21. University of Pretoria, South Africa.

9. Benhin, J.K.A. (2008). South African crop farming and climate change: An economic assessment of impacts. *Global Environmental Change* 18, 666–678.

10. Blignaut, J.N., Ueckermann, L., Aronson, J. (2009) Agriculture production's sensitivity to changes in climate in South Africa. *South African Journal of Science* 105, 61–68.

11. Boko, M., Niang, I., Nyong, A., Vogel, C., Githeko, A., Medany, M. Osman-Elasha, B. Tabo, R., Yanda, P. (2007) Africa. In *Proceedings of the Working Group II Report ―Impacts, Adaptation and Vulnerability‖*; Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E., Eds.; Cambridge University Press: Cambridge, UK.

12. Botai, C.M., Botai, J.O., de Wit, J.C., Ncongwane, K.P., Adeola, A.M. (2017) Drought characteristics over the Western Cape Province, South Africa. *Water* 9, doi:10.3390/w9110876

13. Botai, C.M., Botai, J.O., Dlamini, L.C., Zwane, N.S., Phaduli, E. (2016) Characteristics of droughts in South Africa: A Case Study of Free State and North West Provinces. *Water* 8, doi:10.3390/w8100439.

14. Brown, M.E. (2009) Markets, climate change, and food security in West Africa. *Environ. Sci. Technol 43*, 8016-8020.

15. Chiara, A., Richard, C., Martin, T. (2104) Rainfall-derived growing season characteristics for agricultural impact assessments in South Africa. T*heoretical & Applied Climatology* 115, 411-426.

16. Christensen, J., Hewitson, B.C., Mearns, L.O. (2007) Regional climate projections. In *Climate Change 2007: The Physical Science Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Solomon, S., Qin, D., Manning, M., Eds.; Cambridge University Press: Cambridge, UK.

17. Cleland, E.E., Chuine, I., Menzel, A., Mooney, H.A., Schwartz, M.D. (2007) Shifting plant phenology in response to global change. *Trends Ecol. Evol.* 22, 357–365.

18. Cooper, P.J.M., Dimes, J., Rao, K., Shapiro, B., Twomlow, S. (2008) Coping better with current climatic variability in the rain-fed farming systems of Sub-Saharan Africa: An essential first step in adapting to future climate change? *Agric. Ecosyst. Environ. 126*, 24-35.

19. Crsepo, O., Hachigonta, S., T.adross, M. (2011) Sensitivity of southern African maize yields to the definition of sowing dekad in a changing climate. *Climatic Change* 106, 267-283. Doi: 10.1007/s10584-010-9924-4

20. De Jager, J.M., Potgieter, A,, Van den Berg, W.J. (1998) Framework for forecasting the extent and severity of drought in maize in the Free State province of South Africa. *Agricultural System*. DOI | 10.1016/S0308-521X(98)00023-7.

21. DEA (Department of Environmental Affairs), 2011. South Africa's Second National Communication under the United Nations Framework Convention on Climate Change. Department of Environmental Affairs, Pretoria.

22. Dinar, A., Hassan, R., Mendelsohn, R. Benhin, J. (2008). Climate Change and African Agriculture: Impact Assessment and Adaptation Strategies. *Earthscan*, London.

23. Du Toit, A.S., Prinsloo, M.A., Durand, W., Kiker, G. (2002) Vulnerability of maize production to climate change and adaptation assessment in South Africa. Combined Congress: South African Society of Crop Protection and South African Society of Horticulture Science; Pietermaritzburg, South Africa.

24. Du Toit, M.A., Prinsloo, S., Marthinus, A. (2001) El Nino-Southern Oscillation effects on maize production in South Africa: A preliminary methodology study. In: Rosenzweig, C., Boote, K.J., Hollinger, S., Iglesias A., and Phillips J.G., (Eds). Impacts of El Niño and climate variability on agriculture. *American Society of Agronomy* 63, pp. 77-86.

25. Dube, L.T., and Jury, M.R. (2000) The nature of climate variability and impacts of drought over KwaZulu Natal, South Africa". *South African Geographical Journal* 82, 44-53.

26. Estes, L.D., Beukes, H., Bradley, B.A., Debats, S.R., Oppenheimer, M., Ruane, A.C., Schulze, R., Tadross, M. (2013) Projected climate impacts to South African maize and wheat

production in 2055: a comparison of empirical and mechanistic modeling approaches. *Glob Chang Biol.* 19, 3762-3774.

27. Fanadzo, M., Chiduza, C., Mnkeni, P.N.S. (2009) Investigation of agronomic factors constraining productivity of grain maize (Zea mays L.) at Zanyokwe irrigation scheme, Eastern Cape, South Africa. *Journal of Applied Biosciences* 17, 948-958.

28. Gbetibouo, G.A., Ringler, C., Hassan, R. (2010) Vulnerability of the South African farming sector to climate change and variability: An indicator approach. *Natural Resources Forum* 34, 175–187.

29. Gbetibouo, G., & Hassan, R. (2005) Economic impact of climate change on major South African field crops: A Ricardian approach. *Global and Planetary Change* 47, 143-152.

30. Grayson, M. (2013) Agriculture and drought. *Nature* 501, doi:10.1038/501S1a

31. Hong, X., Tracy, E.T., Xi, Y. (2014) Evaluating remotely sensed phenological metrics in a dynamic ecosystem model. *Remote Sensing* 6, 4660–4686.

32. IPCC, Climate Change (2007) The Physical Science Basis. In Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; Cambridge University Press: Cambridge, UK; New York, NY, USA, [accessed: 10 May 2018].

33. IPCC (2011) Managing the risks of extreme events and disasters to advance climate change adaptation, A special report on working group I and working group II of the intergovernmental panel on climate change. http://www.ipcc.ch/ipccreports/ar4-syr.htm [accessed: 11 May 2018].

34. IPCC (2018) Climate change impacts worse than expected, global report warns, Stephen Leahy. Published October 2018.

35. Jolly, W.M., Running, S.W. (2004) Effects of precipitation and soil water potential on drought deciduous phenology in the Kalahari. *Glob. Chang. Biol*. 10, 303–308.

36. Jury, M.R. (2013) Climate trends in southern Africa. *S Afr J Sci*. 109, http://dx.doi.org/10.1590/ sajs.2013/980.

37. Kang, X., Hao, Y., Cui, X., Chen, H., Huang, S., Du, Y., Li, W., Kardol, P., Xiao, X., Cui, X. (2016) Variability and changes in climate, phenology, and gross primary production of an Alpine Wetland Ecosystem. Remote Sensing 8, 391.

38. Khairunniza-Bejo, S., Mustaffha, S, Wan Ismail, W.I. (2014) Application of Artificial Neural Network in Predicting Crop Yield: A Review. *Journal of Food Science and Engineering* 4, 1-9

39. Kruger, A.C., & Nxumalo, M.P. (2017) Historical rainfall trends in South Africa: 1921–2015. *Water SA*, 43, 285-297. doi.org/10.4314/wsa.v43i2.12.

40. Lee, W.S., Alchanatis, V., Yang, C., Hirafuji, M., Moshoue, D., Lif, C. (2010) Sensing technologies for precision specialty crop production. *Computers and Electronics in Agriculture* 74, 2-33.

41. Mabhaudhi, T., & Modi, A.T. (2010) Early establishment performance of local and hybrid maize under two water stress regimes. *S. Afr. J. Plant & Soil* 27, 299-304.

42. Maddison, D., Manley, M., Kurukulasuriya, P. (2006) The impact of climate change on African agriculture: A ricardian approach. CEEPA Discussion Paper #15. University of Pretoria, South Africa. Physics and Chemistry of the Earth, Parts A/B/C Volume 105, June 2018, pp. 44-51. https://doi.org/10.1016/j.pce.2018.03.009.

43. Maignan, F., Bieon, F.M., Baccour, C., Demarty, J., Poirson, A. (2008) Interannual vegetation phenology estimates from global AVHRR measurements: Comparison with in situ data and application. *Remote Sens. Environ*. 112, 496–505.

44. Malherbe, J., Landman, W.A., Olivier C., Sakuma, H., Luo, J.J. (2014). Seasonal forecasts of the SINTEX-F coupled model applied to maize yield and streamflow estimates over north-eastern South Africa. *Meteorological Applications* 21, 733-742.

45. Masupha, E.T., Moeletsi, M.E., Tsubo, M. (2015) Dry spells with reference to the maize crop in the Luvuvhu River Catchment of South Africa. *Physics and Chemistry of the Earth* 92, 99-111.

46. Masupha, T.E., & Moeletsi, M.E. (2017) Use of standardized precipitation evapotranspiration index to investigate drought relative to maize, in the Luvuvhu River catchment area, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C* 102, 1-9

47. Masupha, T.E., Moeletsi, M.E. (2018) Analysis of potential future droughts limiting maize production, in the Luvuvhu River catchment area, South Africa. *Physics and Chemistry of the Earth* 105, 44-51.

48. Matsumura, K., Gaitan, C.F., Sugimoto, K., Cannon, A.J., Hsieh, W.W. (2015) Maize yield forecasting by linear regression and artificial neural networks in Jilin, China. *Journal of Agricultural Science*, 153, 399-410.

49. Mazvimbakupa, F., Albert, T.M., Mabhaudhi, T. (2015). Seed quality and water use characteristics of maize landraces compared with selected commercial hybrids. Chilean Journal of Agricultural Research 75, http://dx.doi.org/10.4067/S0718-58392015000100002

50. Mendelsohn, R., Dinar, A., Dalfelt, A. (2000). Climate change impacts on African agriculture. http://www.worldbank.org/wbi/sdclimate/pdf.

51. Midgley, G., Chapman, R., Mukheibir, P., Tadross, M., Hewitson, B., Wand, S., Schulze, R., Lumsden, T., Horan, M., Warburton, M., Kgope, B., Mantlana, B., Knowles, A., Abayomi, A., Ziervogel, G., Cullis, R., Theron, A. (2007) Impacts, vulnerability and adaptation in key South African sectors. An input into the Long Term mitigation scenarios process. South Africa: Energy Research Centre, University of Cape Town.

52. Moeletsi, M.E. (2017) Mapping of maize growing period over the Free State Province of South Africa: Heat Units Approach. *Advances in Meteorology* 2017, 1-11. https://doi.org/10.1155/2017/7164068.

53. Moeletsi, M.E, & Walker, S. (2012) Rainy season characteristics of the Free State Province of South Africa with reference to rain-fed maize production. *Water SA* 38, http://dx.doi.org/10.4314/wsa.v38i5.17.

54. Moeletsi, M.E., Walker, S., Landman, W.A. (2011) ENSO and implications on rainfall characteristics with reference to maize production in the Free State Province of South Africa. *Physics and Chemistry of the Earth* 36, 715-726.

55. Mpandeli, N.S. (2005) Coping with climate variability in Limpopo Province. Sustainable Rural Livelihoods Technical Report.

56. Ngie A, Ahmed F. Estimation of Maize grain yield using multispectral satellite data sets (SPOT 5) and the random forest algorithm. *South African Journal of Geomatics. 2018, 7.* http://dx.doi.org/10.4314/sajg.v7i1.2.

57. Pawson, R., Greenhalgh, T., Harvey, G., Walshe, K. (2005) Realist review - A new method of systematic review designed for complex policy interventions. *J. Health Res. Policy 10*, 21-34.

58. Pereira L. (2017) Climate change impacts on Agriculture across Africa. Oxford Research Encyclopedia of Environmental Science.

59. Rankoana S.A. (2016) Perceptions of climate change and the potential for adaptation in a rural community in Limpopo Province, South Africa. *Sustainability* 8, 672-688. doi:10.3390/su8080672.

60. Robert, M., Eyob, T.B., Gianni, B.C., Abubeker, H. (2018) Modelled impacts of extreme heat and drought on maize yield in South Africa. *Crop and Pasture Science* 69, 703-716. https://doi.org/10.1071/CP18117

61. Robert, M., Eyob, H.T., Gianni, B.C., Abubeker, H. (2018) Growth development, leaf gaseous exchange, and grain yield response of maize cultivars to drought and flooding stress. S*ustainability* 10, 3492

62. Rouault, M., Richard, Y. (2003) Intensity and spatial extension of drought in South Africa at different time scales. *Water SA* 29, 489–500.

63. Schulze, R.E., Kiker, G.A., Kunz, R.P., (1993) Global climate change and agricultural productivity in Southern Africa. *Global Environmental Change* 3, 330–349.

64. Steynberg, R.E., Nel, P.C., Hammes, P.S. (1989) Drought sensitivity of maize (Zea mays L.) in relation to soil fertility and water stress during different growth stages. *South African Journal of Plant and Soil* 6, 83-85

65. Tadross, M.A, Hewitson, B.C, Usman, M.T. (2003) The interannual variability of the onset of the maize growing season over South Africa and Zimbabwe. *Journal of Climate* 18, 3356-3372.

66. Vogel, C., & Reid, P. Vulnerability, adaptive capacity, coping and adaptation: A conceptual framework. In *Climate Change and Water Resources in Southern Africa*, Studies on Scenarios, Impacts, Vulnerabilities and Adaptation. Pp 352-358. Schulze RE (ed.). Water Research Commission, Pretoria, South Africa Report 2005. 1430/1/05.

67. Vrieling, A., Jan de Leeuw, Said, M.Y. (2013) Length of growing period over Africa: variability and trends from 30 years of NDVI time series. *Remote Sensing* 5, 982-1000.

68. Walker, N. & Schulze, R. (2006) An assessment of sustainable maize production under different management and climate scenarios for smallholder agro-ecosystems in KwaZulu-Natal, South Africa. *Physics and Chemistry of the Earth Parts A/B/C* 31, 995-1002.

69. Walker, N.J., & Schulze, R.E. (2008) Climate change impacts on agro-ecosystem sustainability across three climate regions in the maize belt of South Africa. *Agriculture, Ecosystems and Environment* 124, 114–124.

70. Wasserman, I.C., & Kram, K.E. (2009) Enacting the scholar-practitioner role: an exploration of narratives. *J Appl Behav Sci*. 45, 12–38

71. Wilhite, D.A. (2000) Drought: A global assessment, Vols. 1 and 2. Routledge, NewYork, 89-104, 1 and 2, Routledge, New York; 129-448.

72. Wilhite, D.A. (1992) Preparing for drought: a guidebook for developing countries, Climate Unit, United Nations Environment Program, Nairobi, Kenya.

73. Yang, M., Yan, D., Yu, Y., Yang, Z. (2015) SPEI-based spatiotemporal analysis of drought in haihe river basin from 1961 to 2010. *Advances in Meteorology* 2016, 1-10. http://dx.doi.org/10.1155/2016/7658015.

74. Zhang, Q., & Zhang, J. (2016) Drought hazard assessment in typical corn cultivated areas of China at present and potential climate change. *Nat. Hazards* 81, 1323-1331.

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

Chapter 3

IMPACT OF AGRO-CLIMATIC PARAMETERS ON MAIZE PRODUCTION

Analysis of agro-climatic parameters and their influence on maize production in South Africa

***Omolola M. Adisa*[1,*]**, Christina M. Botai[2], Joel O. Botai[1,2], Abubeker Hassen[3], Daniel Darkey[1], Eyob Tesfamariam[4], Alex F. Adisa[5], Abiodun M. Adeola[2], Katlego P. Ncongwane[2]

[1]Department of Geography, Geoinformation and Meteorology, University of Pretoria, Hatfield, South Africa. lolaadisa@yahoo.com; daniel.darkey@up.ac.za; joel.botai@up.ac.za;

[2]South African Weather Service, Erasmusrand, Pretoria, South Africa. christina.botai@weathersa.co.za; joel.botai@weathersa.co.za; abiodun.adeola@weathersa.co.za; katlego.ncongwane@weathersa.co.za;

[3]Department of Animal and Wildlife Sciences, University of Pretoria, South Africa. abubeker.hassen@up.ac.za;

[4]Department of Plant Science, University of Pretoria, Hatfield, South Africa. eyob.tesfamariam@up.ac.za;

[5]Department of Agricultural Engineering, Federal University of Agriculture, Abeokuta, Nigeria alexadisa@yahoo.co.uk;

* Corresponding author. lolaadisa@yahoo.com

This article has been published in Theoretical and Applied Climatology, https://link.springer.com/article/10.1007/s00704-017-2327-y

---

Abstract:

This study analysed the variability of the agro-climatic parameters that impact maize production across different seasons in South Africa. To achieve this, four agro-climatic variables (precipitation, potential evapotranspiration, minimum and maximum temperatures) were considered for the period spanning 1986 – 2015, covering the North West, Free State, Mpumalanga and KwaZulu-Natal (KZN) provinces. Results illustrate that there is a negative trend in precipitation for North West and Free State provinces and positive trend in maximum temperature for all the provinces over the study period. Further more, the result showed that among other agro-climatic parameters, minimum temperature had the most influence on maize production in North West, potential evapotranspiration (combination of the agro-climatic parameters), minimum and maximum temperature influenced maize production in KwaZulu-Natal while maximum temperature influenced maize production in Mpumalanga and Free State. In general, the agro-climatic parameters were found to contribute 7.79 %, 21.85 %, 32.52 % and 44.39 % to variation in maize production during the study period in North West, Free State, Mpumalanga and KwaZulu-Natal respectively. The variation in maize production amongst the provinces under investigation could most likely attributed to the variation in the size of the cultivated land among other factors including soil type and land tenure system. There were also difference in yield per hectare between the provinces; KwaZulu-Natal and Mpumalanga being located in the humid subtropical areas of South Africa had the highest yield per hectare 5.61 tons and 4.99 tons respectively while Free State and North West which are in the semi-arid region had the lowest yield per hectare 3.86 tons and 3.03 tons respectively. Understanding the nature and interaction of the dominant agro-climatic parameters discussed in the present study as well as their impact on maize production will help farmers and agricultural policy makers to understand how climate change exerts its influence on maize production within the study area so as to better adapt to the major climate element that either increases or decreases maize production in their respective provinces.

Keywords: Maize, production, yield, multivariate regression, climate variables

3.0. Introduction

Change in climate has substantial impacts on human health, hydropower, food security, water resources and so on, at local and global scale (Magadza. 2000). Climatic parameters such as solar radiation, air humidity, precipitation, temperature, and wind speed, often determine the global distribution and productivity of crops and livestock (Ajadi et al. 2011). Hence, climate change and variability is foreseen to have direct and indirect effects on the existing agricultural production systems potentially threatening local, regional and/or global food security (Ajadi et al. 2011), depending on the spatial scale of the change. The trend and level of impact due to climate change and/or variability is region dependent (FAO 2013). In areas, where rainfall is the limiting factor for production, an increase in rainfall amount and distribution with little or no change in rainfall intensity and atmospheric temperature may increase crop yield. While excessive increase in rainfall intensity beyond the soil's infiltration rate may lead to runoff losses and erosion (Hawkins 1981) further negatively affecting agricultural production due to loss of the top fertile soil (Wenbin et al. 2015). Similarly, an increase in temporal rainfall amount beyond the soil's capacity to retain water in the active root zone may lead to excessive nitrate leaching beyond the reach of the plant roots (Tesfamariam et al. 2015). Such excessive nitrate leaching beyond the crop root system leads to nitrogen deficiency (reduced crop production) and the leached nitrate may cause ground water contamination (Suresh et al. 2017). In contrast, a reduction in the amount and distribution of rainfall during the sensitive growth stages of crops has detrimental effects on crop yield (Tesfamariam et al. 2010). Similar to rain, a change in atmospheric temperature has its own impact on crop yield. For instance, an increase in temperature from 30 ^{o}C to $\geq$ 35 ^{o}C during the reproductive stage in most photoperiod sensitive crops will adversely affect the pollen viability, fertilization and consequently grain formation, hence lending to a decrease in productivity (Hatfield et al, 2008; 2011).

The impacts of climate change on crop production can no-longer be ignored as they have already become key areas of scientific concern (Yinhong et al. 2009). Such impacts are becoming increasingly significant in the arid and semi-arid areas, particularly in Africa, which comprises of 66 % of the total land area, and harbouring approximately 200 million people (Molua et al. 2010). South Africa is a semi-arid country with about two-third of its land area receiving a mean annual rainfall of less than 500 mm (Durand 2006). More than a million people in South Africa are directly dependent on agriculture for their livelihood. Rainfall variability and high temperatures are currently the most significant elements of climate change in South Africa that are expected to have a severe impact on agriculture (Durand 2006, Botai et al. 2016). For instance, climate projection studies have indicated that the frequency of droughts is likely to increase spontaneously with a higher spatial variability in rainfall, consequently resulting in a negative effect on farm production

(IPCC 2007). Studies by Erasmus et al. (2000) on modelling future climate change in the Western Cape alluded that future climate change may lead to lower precipitation, implying that less water will be available for agriculture in the province and consequently leading to a negative effect on the farm economy. With an increase in mean temperature by 0.13 ^{o}C between 1960 and 2003 (Kruger and Shongwe 2004), an expected further increase of 1.2 ^{o}C in 2020, 2.4 ^{o}C in 2050 also 4.2 ^{o}C by the year 2080 and a projected rainfall decrease of about 5-10 percent in the next 50 years (Hewitson 1999; Durand 2006), South Africa is expected to have food insecurity soonest.

Previous studies on the potential impact of climate change on field crop production in southern Africa indicated that different crops respond differently to the envisaged change in climate. (Schulze et al. 1993; Chipanshi et al. 2003; Fischer et al. 2005; Thornton et al. 2011). Schulze et al. (1993), developed an analysis tool to simulate primary productivity and crop yields under different climatic conditions in southern Africa. The results reported an overall increase in potential maize production that corresponds to an increased carbon dioxide and temperature conditions. Du Toit et al. (2001) assessed the vulnerability of maize production to climate change in South Africa and found that maize production in the country is characterized by high variations in crop yield that manifest from changes in seasonal precipitation. Gbetibouo and Hassan (2005) used a Ricardian model to assess the impacts of climate change on seven field crops (maize, wheat, sorghum, sugarcane, groundnut, sunflower and soybean) in South Africa. The authors reported that the production of field crops was sensitive to marginal changes in temperature than to changes in precipitation, whereby an increase in temperature positively affects the net revenue whereas a reduction in rainfall negatively affect the net revenue. Similar studies by Deressa et al. (2005) alluded that climate change has significant nonlinear impacts on the net revenue of sugarcane production in South Africa, with higher sensitivity to increasing temperature than precipitation.

Maize is one of the rain-fed summer field crops grown in South Africa with a 3 % annual increase in demand (Durand 2006). In particular, maize production covers 58 % of the cropping area in southern Africa (Schulze et al. 1993), with South Africa producing 50 % of this main staple crop in the Southern African Development Community (SADC) region (Molua and Lambi 2006), hence making the country the major source of food in the region (FAO 2010). In addition, maize plays a crucial role in red-meat production by contributing up to 50 % of feedlot diet (Department of Agriculture, Forestry and Fisheries, 2015). Contributing about R9.4 billion per annum to the economy, it is conclusively acknowledged that maize production plays an essential role on the

South African economy in general and food security in particular. However, most (approximately 60 %) of the maize is produced in the drier region of South Africa (Molua and Lambi 2006). The limiting factor to maize production in South Africa is water availability, whereby approximately 60 % of this scarce resource are used for irrigation (James 2009). In particular, climate variability has a significant impact on maize production emanating from seasonal rainfall and temperature which are responsible for the shifting of the seasons. Such effects pose a potential threat to small scale farmers in South Africa as they are likely to face challenges of crop failures and reduced maize productivity which may consequently lead to hunger, malnutrition and spread of diseases (Wisdom et al. 2008; Jill et al. 2013).

Generally, on-going climate change impacts will indisputably hamper agricultural output and contribution of the agricultural sector to South African's Gross Domestic Production (GDP) and food security, and therefore potentially destabilizing not only the country but eventually the whole SADC region. This implies that, climate change influences on maize production in South Africa can no-longer be underestimated, given the ultimate consequences of such impacts. Despite numerous research studies on the impact of climate change on crop production in South Africa, most of these studies were models based (such as crop processing models, statistical models and econometric models). These models fail to determine the dominant weather variable(s) contributing to the change observed on maize production under different climate conditions. The aim of this study is to characterize the spatio-temporal agro-climatic patterns across the four South Africa maize producing provinces and to determine the most dominant climatic parameter influencing maize production in each of the provinces. Acknowledging that most of the climate variables are beyond the control of the farmers, this study seeks to contribute towards achieving proper climate adaptation practices by farmers, in a bid to minimize the adverse effects of climate change on maize production. To the best of our knowledge, this study is unique and rarely reported in the literature considering the study regions, the set of parameters selected and the analysis methodology adopted.

3.1. Study Area

The study area covers Free State (FS), North West (NW), Mpumalanga (MP) and KwaZulu-Natal (KZN) provinces of South Africa, see Fig 1. The study area is located in the north-eastern part of South Africa between 22^{o}E to 33^{o}E and -32^{o}S to -24^{o}S longitude and latitude, respectively. The four selected provinces are the largest producers of maize in the country, accounting for approximately 83% of the total production. The four regions can be further divided into the dry west and the wet east, whereby approximately 60 % of the maize produced is from the dry western areas the rest comes from the eastern areas. The Free State and North West provinces are the highest maize producers, contributing more than 60% of the total maize production in South Africa, followed by Mpumalanga (~24 %) and KZN (less than 5 %). South Africa's climate conditions range from Mediterranean in the south-western corner of South Africa to temperate in the interior plateau and subtropical in the northeast, with small area in the northwest exhibiting a desert climate. According to Koppen climate classification (Kottek et al. 2006), shown in Table 1, climate conditions within the selected study region range between cold, temperate and subtropical conditions. Rainfall exhibit seasonal distribution, with all the four selected provinces receiving summer rainfall. In particular, the North West and Free State provinces receive total annual rainfall of less than 500 mm whereas Mpumalanga and KZN receive between 500 mm and 800 mm. The annual mean maximum temperature for the four provinces is 25 ^{o}C, while the annual mean potential evapotranspiration is 3.7 mm/day.

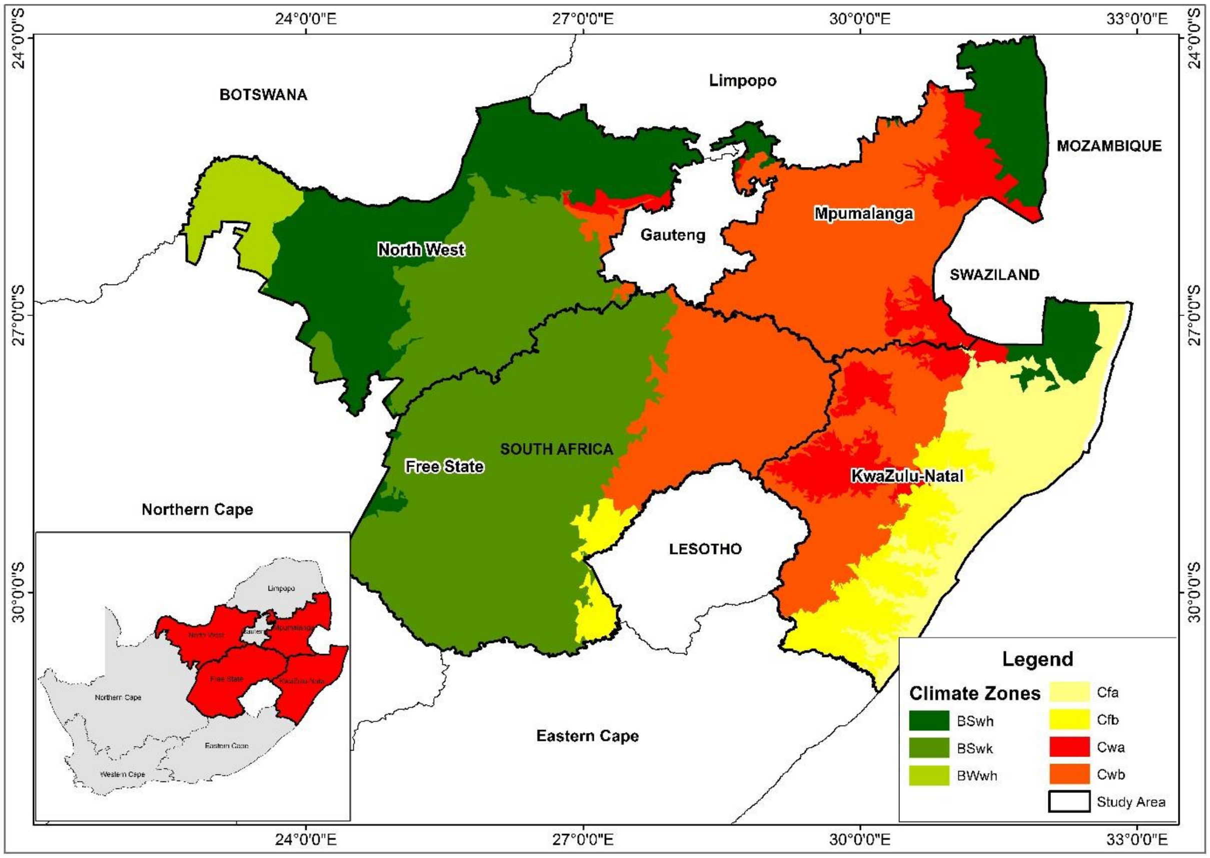

Figure 3-1: Map of seven Southern African countries with inset showing the provinces division

Table 3-1: South African Koppen Climate Classification (Interpretation of Fig 1 legend) (Kottek et al. 2006). North West (NW), Mpumalanga (MP), KwaZulu-Natal (KZN) and Free State (FS)

Provinces	**Description of the climate/ codes**	**Annual Precipitation (mm)**	**Annual Temperature °C**	
			Summer	**Winter**
NW	Largely Semi-arid *(BSwh, BSwk, Cwa & Cwb)*	250 - 500	17 - 31	3 - 21
MP	Largely Humid Subtropical *(BSwh, Cwa, & Cwb)*	500 - 850	12 - 29	1 - 23
KZN	Largely Humid Subtropical *(BSwh, Cfa, Cfb, Cwa, & Cwb)*	500 - 850	21 - 28	11 - 23
FS	Largely Semi-arid *(BSwk, Cfb, & Cwb)*	250 - 650	13 - 31	-2 - 16

3.2. Data and Method

3.2.1. Climate data

This study analysed the latest updated gridded climate dataset, the Climate Research Unit Time-Series 3.24.01 (CRU TS 3.24.01) for the period spanning 1986 – 2015. The CRU TS climate data are derived from monthly observations from more than 4000 meteorological stations distributed across the world's land areas. The gridded CRU TS 3.24.01 product is freely available for science community on http://www.cru.uea.ac.uk or http://badc.nerc.ac.uk/data/cru. For more information on the construction of the CRU TS 3.24.01 product, the reader is referred to Harris et al. (2014). The climate variables included in the CRU TS 3.24.01 are the mean temperature, diurnal temperature range, precipitation, wet-day frequency, vapour pressure, and cloud cover. These climate variables were further used to arithmetically derive the monthly maximum and minimum temperature. For the purpose of this study, only four variables were analysed for the period spanning 1986 – 2015. These variables are precipitation (PRE), potential evapotranspiration (PET) (note* PET was calculated based on the Penman-Monteith formula (Howard Penman and John Monteith) using gridded daily mean temperature (TMP), monthly average daily minimum temperature (TMN), monthly average daily maximum temperature (TMX), vapour pressure (VAP) and cloud cover (CLD)) and monthly average daily maximum and minimum temperature, (TMX) and (TMN), respectively.

3.2.2. Maize data

Maize production data sets in tonnes (here after tons) for each selected province spanning from 1986 to 2015 were obtained from the Abstract of Agricultural Statistics compiled by the Department of Agriculture, Forestry and Fisheries of South Africa. This abstract document contains important information on *inter alia*, field crops, horticulture, livestock, vital indicators and the contribution of primary agriculture to the South African economy. The analysed data are available on the department's website, www.daff.gov.za. Additionally, total land area hectare (here after ha) cultivated for maize production in the provinces is only available from 2002 to 2015 and was acquired from Grain South Africa. Hence, total yield/ha was calculated (Production data in tons divide by Land cultivated in ha for 2002 to 2015).

3.3. Methodology

3.3.1. Spatial-temporal characteristics of agro-climatic parameters

In this study, agro-climatic parameters, e.g. PRE, PET, TMX and TMN were analysed to understand the inherent spatio-temporal characteristics of each parameter. The statistical properties of the computed data series (that is PRE, PET, TMX, TMN, maize production and the average yield per hectare) were described based on the mean, standard deviation, and coefficient of variation as a measure of variability. This is presented in tabular format and boxplot.

3.3.2. Trends

The processing of these agro-climatic parameters were performed by converting the monthly time series of climatic parameters into annual and seasonal data series across the four selected provinces. The monthly, annual and seasonal time series data were analysed to assess the trends of the agro-climatic parameters during 1986 – 2015. To compute the trends, the regional kendall test (rkt) package in R software was used, which helps to calculate the Mann-Kendall (MK) as well as the Seasonal and Regional Kendall Tests for trend (SKT and RKT) also the Theil-Sen's slope. The three tests (MK, SKT and RKT) are usually used to test for monotonic trends (that is consistent increase or decrease trend over the years) in a time series data based on the kendall rank correlation. The RKT and SKT are intra-block tests in which test statistics are computed for each month or season (SKT) otherwise for each year (RKT) all combined in a single test (Marchetto et al. 2013). The two sided *p*-value from the result of this analysis is used to ascertain the significant difference in the monthly, seasonal and annual agro-climatic parameters as well as annual maize production. From the output we were able to determine which climatic parameter or maize production is statistically significant ($p \leq 0.05$). In this method, the null hypothesis (H_0), (rejected when $p \leq 0.05$), is that there is no trend in the population from which the dataset is drawn. The alternative hypothesis (H_1) is that there is a trend in the population.

3.3.3. Seasonal variation

In order to understand the impact of each agro-climatic parameter on maize production across different seasons, multiple coefficient of determination (r^2) analysis was used. The r^2 is a statistic that explains the amount of variance accounted for, in the relationship between two (or more) variables. Thus, given a paired of variables (X_i, Y_i), a linear model given in Equation (1) can be used to explain the relationship between the two variables,

$$Y = \beta_0 + \beta_1 X + e \qquad \text{Eq. 1}$$

where *e* is a mean zero error. The parameters of the linear model can be estimated using the least squares method and the estimated model can be denoted as per Equation (2),

$$\hat{Y} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 X \qquad \text{Eq. (2)}$$

The sum of squared errors or residuals (SSE) and the total sum of squares (SST) in the Y are derived from Equation (3) and Equation (4), respectively

$$SSE = \sum_{i=1}^{n} Y_i^2 - \boldsymbol{\beta}_0 \sum_{i=1}^{n} Y_i - \boldsymbol{\beta}_1 \sum_{i=1}^{n} X_i Y_i \quad \text{Eq. (3)}$$

and

$$SST = \sum_{i=1}^{n} Y_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} Y_i\right)^2 \quad \text{Eq. (4)}$$

The coefficient of multiple determination is given by Equation (5)

$$r^2 = \frac{SST - SSE}{SST} \quad \text{Eq. (5)}$$

Equation (5) can also be expressed as a function of the sample cross-covariance as follows,

$$r^2 = \frac{{S_{xy}}^2}{S_{xx} S_{yy}} = \frac{(\overline{XY} - \bar{X}\bar{Y})^2}{(\overline{X^2} - \bar{X}^2)(\overline{Y^2} - \bar{Y}^2)} \quad \text{Eq. (6)}$$

where $SSE = nS_{yy} - n\frac{{S_{xy}}^2}{Sxx}$ and $SST = nS_{yy}$

Equation (6) corresponds to the square of the Pearson product moment correlation coefficient,

$$r = \frac{S_{xy}}{\sqrt{S_{xx}}\sqrt{S_{yy}}} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{X})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X}) \sum_{i=1}^{n}(Y_i - \bar{Y})}} \quad \text{Eq. (7)}$$

In this contribution, using the multiple coefficient of determination analysis given in Equation (6), we wish to characterize to which extent the agro-climatic variables (here represented by variable X) affect maize production in the four of the selected provinces in the same season. For this purpose, the selected seasons were December and January (DJ, also considered as the early phase), December, January and February (DJF, the middle phase), February and March (FM, the late phase) and November, December, January, February and March (NDJFM).

3.3.4. Multivariate analysis

Multivariate linear regression analysis of climatic variables (PRE, PET, TMN and TMX) and crop yield anomalies were calculated with the objective to describe the dependence of the maize production on the predictor variables (here selected as the agro-climatic variables). In particular, the multivariate regression analysis performed in this study can be explained by a linear model given in Equation (8).

$$\Delta Y = \varepsilon + (\alpha \times \Delta PRE) + (\beta \times \Delta PET) + (\gamma \times \Delta TMN) + (\delta \times \Delta TMX) \quad \text{Eq. (8)}$$

where ΔY corresponds to the observed change in the yield as a result of precipitation, potential evapotranspiration and temperature (minimum and maximum) in the season as maize growth. In addition, ε is a constant and α, β, γ and δ are coefficients of the precipitation, potential evapotranspiration, minimum temperature and maximum temperature during the season, respectively. Furthermore, ΔPRE, ΔPET, ΔTMN and ΔTMX are the observed changes in precipitation potential evapotranspiration, minimum and maximum temperatures of the seasons, respectively, during 1986 – 2015.

3.4. Results

3.4.1. Spatial-temporal characteristics

Table 2 provides a descriptive statistic of the mean value of maize production annually in tons (1986-2015), land area in ha (2002-2015), annual maize yield/ha (2002 to 2015) and the seasonal mean value (NDJFM) of selected agro-climatic parameters for four South African provinces spanning from 1986 to 2015. The maize production for Free State was the highest of all the four provinces with a mean production of about 3,365,400 tons (1986-2015) and a mean of about 4,002,357 tons (2002-2015) from an area of about 1,036,000 ha. The annual average of maize yield for Free State province was 3.86 tons/ha (2002-2015). The province received an annual mean precipitation of 81.01 mm/month; mean potential evapotranspiration of 5.12 mm/day; and the minimum temperature and maximum temperature were 13.92 ^{o}C and 28.63 ^{o}C, respectively for NDJFM. North West had the second largest mean maize production of about 2,399,570 tons/annum (1986-2015) and about 2,241,357 tons/annum (2002-2015) on a land area of about 748,000 ha. The annual maize yield for North West was an average of 3.03 tons/ha (2002-2015). Between 1986 and 2015, North West province received an annual mean precipitation amount of 74.84 mm/month; mean potential evapotranspiration of 5.25 mm/day; minimum temperature and maximum temperature of 16.36 ^{o}C and 30.72 ^{o}C respectively during NDJFM. In Mpumalanga province, the annual mean maize production was about 2,104,730 tons (1986-2015) and 2,400,857 tons (2002-2015) on mean land area of about 484,000 ha. The province has an annual average of maize yield of 4.99 tons/ha making it the second largest province in maize yield/ha. During the whole period under investigation, Mpumalanga recorded an annual mean precipitation of about 130.42 mm/month; potential evapotranspiration of 3.81 mm/day; minimum temperature of about 14.02 ^{o}C and maximum temperature of 25.25 ^{o}C during the NDJFM months. KwaZulu-Natal recorded the lowest mean maize production of about 380,800 tons (1986-2015) and 463,429 tons (2002-2015) with an average land area of 82,000 ha (2002-2015). The province has the highest maize yield with an average of 5.61 tons/ha. For the period understudy, KZN received a mean annual precipitation of 124.37 mm/month; potential evapotranspiration of 3.88 mm/day; minimum temperature of 15.88 ^{o}C and maximum temperature of 26.74 ^{o}C.

Considering the variation in maize production and the agro-climatic parameters from the mean values in table 2 (variance) and Fig 3 (box plot), maize in Free state had the highest level of variation with a variance of 1,476,903, followed by North West (715,721.7), Mpumalanga (283,016.8) and KwaZulu-Natal (10,408.8) recorded the lowest variation. Likewise, there is great difference in the maize yield value across the provinces (Fig 2).

Agro-climatically, high variation in precipitation is noticed in Mpumalanga (864.89) when compared to the other three provinces (Table 2 and Fig 2). For potential evapotranspiration, North West and Free State experienced almost the same high level of variation (0.07 and 0.06 respectively) within the provinces compared to the other two provinces. In the case of minimum temperature and maximum temperature Free State exhibited the highest variability compared to the other provinces.

Furthermore, the precipitation values for Mpumalanga and KwaZulu-Natal were almost equal, this could be attributed to the fact that they are in the same climatic zone (Humid Subtropical). Similarly, North West and Free State provinces which have semi-arid climatic conditions exhibit same first order statistical moment. For instance, the potential evapotranspiration mean values of Mpumalanga and KwaZulu-Natal are similar and that of North West and Free State are similar as well. But minimum and maximum temperature values, the results are contrasting across the provinces.

Table 3-2: Maize yield and selected agro-climatic parameters for four South Africa provinces. precipitation (PRE) mm/month; potential evapotranspiration (PET) mm/day; monthly average daily minimum temperature (TMN) ^{o}C; monthly average daily maximum temperature (TMX) ^{o}C

Table 2a: North West				**Table 2b: Mpumalanga**			
Variable	**Mean**	**STD**	**Variance**	**Variable**	**Mean**	**STD**	**Variance**
Maize Prod	2399.57	846	715721.7	**Maize Prod**	2104.73	532	283016.8
PRE	74.84	18.93	308.32	**PRE**	130.42	29.41	864.89
PET	5.25	0.27	0.07	**PET**	3.81	0.18	0.03
TMN	16.36	0.52	0.27	**TMN**	14.02	0.42	0.18
TMX	30.72	1.05	1.10	**TMX**	25.25	0.79	0.63
Land	747.79	179.21	32116.49	**Land**	484.21	58.17	3384.18

Maize Yield	3.03	0.77	0.60	Maize **Yield**	4.99	0.95	0.91
Table 2c: KwaZulu-Natal				**Table 2d: Free State**			
Variable	**Mean**	**STD**	**Variance**	**Variable**	**Mean**	**STD**	**Variance**
Maize Prod	380.8	102	10408.8	**Maize Prod**	3365.4	1215.3	1476903
PRE	124.37	23.83	567.84	**PRE**	81.01	19.40	376.22
PET	3.88	0.17	0.03	**PET**	5.12	0.25	0.06
TMN	15.88	0.40	0.16	**TMN**	13.92	0.65	0.43
TMX	26.74	0.6	0.36	**TMX**	28.63	1.06	1.11
Land	82.48	8.45	71.36	**Land**	1035.79	200.83	40333.26
Maize Yield	5.61	0.61	0.37	Maize **Yield**	3.86	0.73	0.53

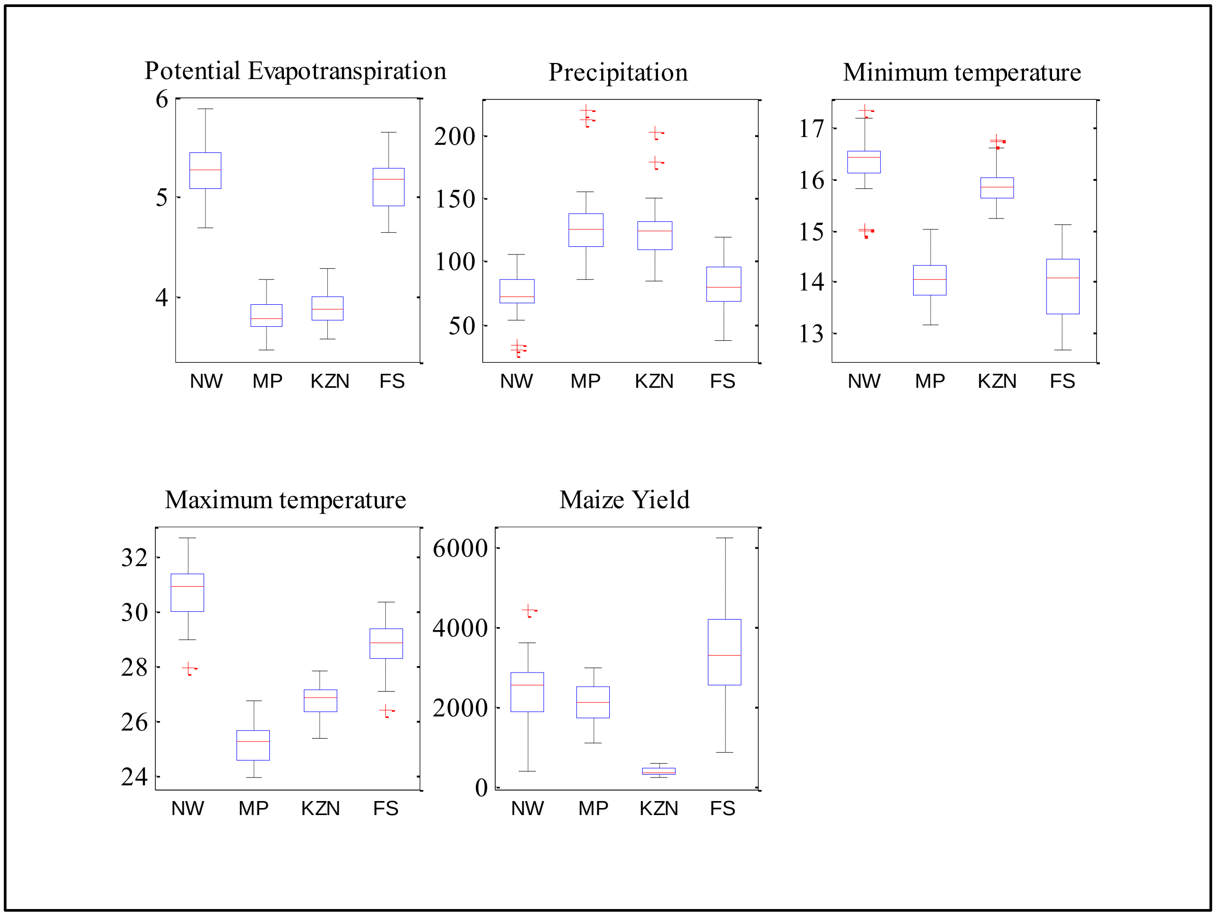

Figure 3-2: Overall median properties of Potential evapotranspiration (mm/day), Precipitation (mm), Minimum temperature and Maximum temperature (oC) (1986-2015): Maize yield is compared for 2002-2015

Shown in Fig 3 is the variation in maize production against cultivated land for maize from 2002-2015. The figure depicts that there is a similar pattern noticed between maize production (tons) and amount of cultivated land (ha). Increase in cultivated acreage to depicts increase in production across all provinces and vice versa. This is to say that when more land is cultivated for maize production there is an increase in the maize production and when less portion of land is cultivated, production tends to reduce. There is a strong positive correlation of 0.77 and 0.84 between maize production and cultivated land for maize in Free State and KZN respectively. While a moderate positive relationship (0.55) in North West and a weak positive relationship (0.33) in Mpumalanga exist between maize production and acreage. This similar variation in production and cultivated land can be held to be the same for previous years (1986-2001) in which cultivated land data is not available at provincial level. Hence, agro-climatic parameters can be said to be comparable with production data if land is held in constant variation with production.

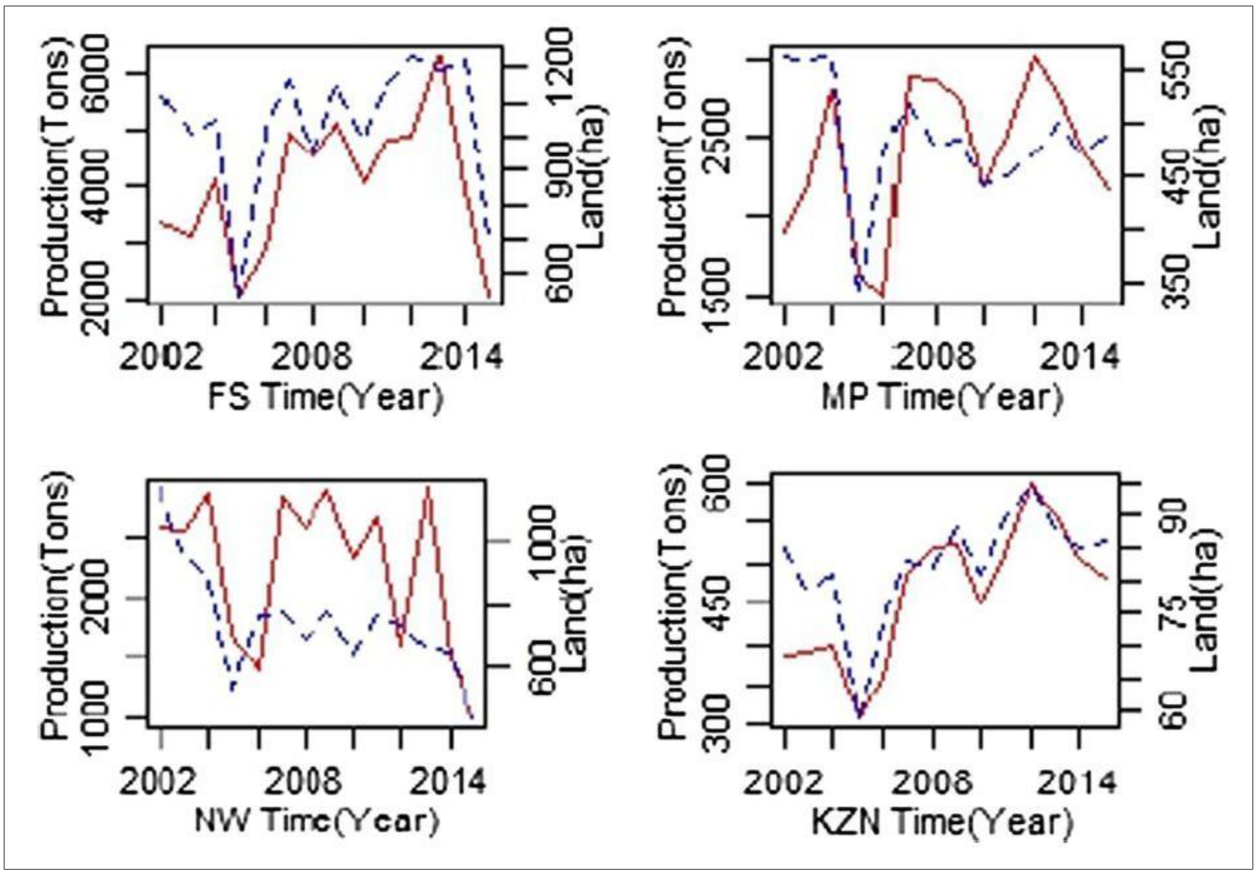

Figure 3-3: Variation in maize production and acreage (Plot of time series of maize production (tons) on left Y-axis (Red line) and time series of cultivated land for maize (h) (right Y-axis) (dashed Blue line) 2002-2015)

3.4.2. Trend analysis

For the 30-year study period, the monthly values (Fig 4a) shows that there is a negative trend in precipitation across the four provinces. Precipitation in North West decreased by 0.0018 mm/month, Mpumalanga by 0.012 mm/month, KwaZulu-Natal by 0.0062 mm/month and in Free State by 0.0135 mm/month. On the other hand, there is positive trend in potential evapotranspiration in all the provinces, indicating that North West's PET increased by 0.0009 mm/day, Mpumalanga and KwaZulu-Natal by 0.0004 mm/day and Free State by 0.0007 mm/day. Similarly, maximum temperature increased in North West by 0.0059 ^{o}C, Mpumalanga by 0.0032 ^{o}C, KwaZulu-Natal by 0.0029 ^{o}C and Free State by 0.0046 ^{o}C. The minimum temperature exhibited different patterns in trends among the provinces: it showed increasing trend in North West by 0.0006 ^{o}C, declining trend in Mpumalanga by 0.0004 ^{o}C and no change in KwaZulu-Natal and in Free State.

On seasonal time scales, shown in Fig 4b, the result indicates a negative trend in the precipitation received in North West and Free State (decrease of 0.35 mm/month and 0.04 mm/month respectively) while precipitation for Mpumalanga and KwaZulu-Natal (increase of 0.38 mm/month and 0.27 mm/month respectively) had a positive trend. On other hand, maximum temperature had a positive trend in all the provinces; North West increased by 0.054 ^{o}C, Mpumalanga by 0.036 ^{o}C, KwaZulu-Natal by 0.034 ^{o}C and Free State by 0.028 ^{o}C. Similarly, potential evapotranspiration had a positive trend for all the provinces where North West increased by 0.0113 mm/day, Mpumalanga by 0.004 mm/day, KwaZulu-Natal by 0.005 mm/day and Free State by 0.006 mm/day. Minimum temperature exhibited a different pattern in trends among the provinces: it showed an increase in TMN for North West, Mpumalanga and KwaZulu-Natal by 0.01 ^{o}C, 0.0009^{o}C and 0.0002 ^{o}C respectively while the minimum temperature for Free State decreased by 0.006 ^{o}C during the study period.

Furthermore, as shown in Fig 4c, the annual values of precipitation decreased in all the provinces; North West by 0.255 mm/month, Mpumalanga by 0.192 mm/month, KwaZulu-Natal by 0.235 mm/month and Free State by 0.341 mm/month. Maximum temperature increased over the years for all the provinces (North West by 0.064 ^{o}C, Mpumalanga by 0.04 ^{o}C, KwaZulu-Natal by 0.0375 ^{o}C and Free State by 0.054 ^{o}C). Potential evapotranspiration had a positive trend in all the provinces. There was an increase of about 0.01 mm/day in North West, 0.006 mm/day in Mpumalanga, 0.0053 mm/day in KwaZulu-Natal and 0.0083 mm/day in Free State. In addition, annual minimum temperature values increased in North West and Free State by 0.0067 ^{o}C and 0.01^{o}C respectively and decreased by 0.0075 ^{o}C in Mpumalanga and 0.0011^{o}C in KwaZulu-Natal.

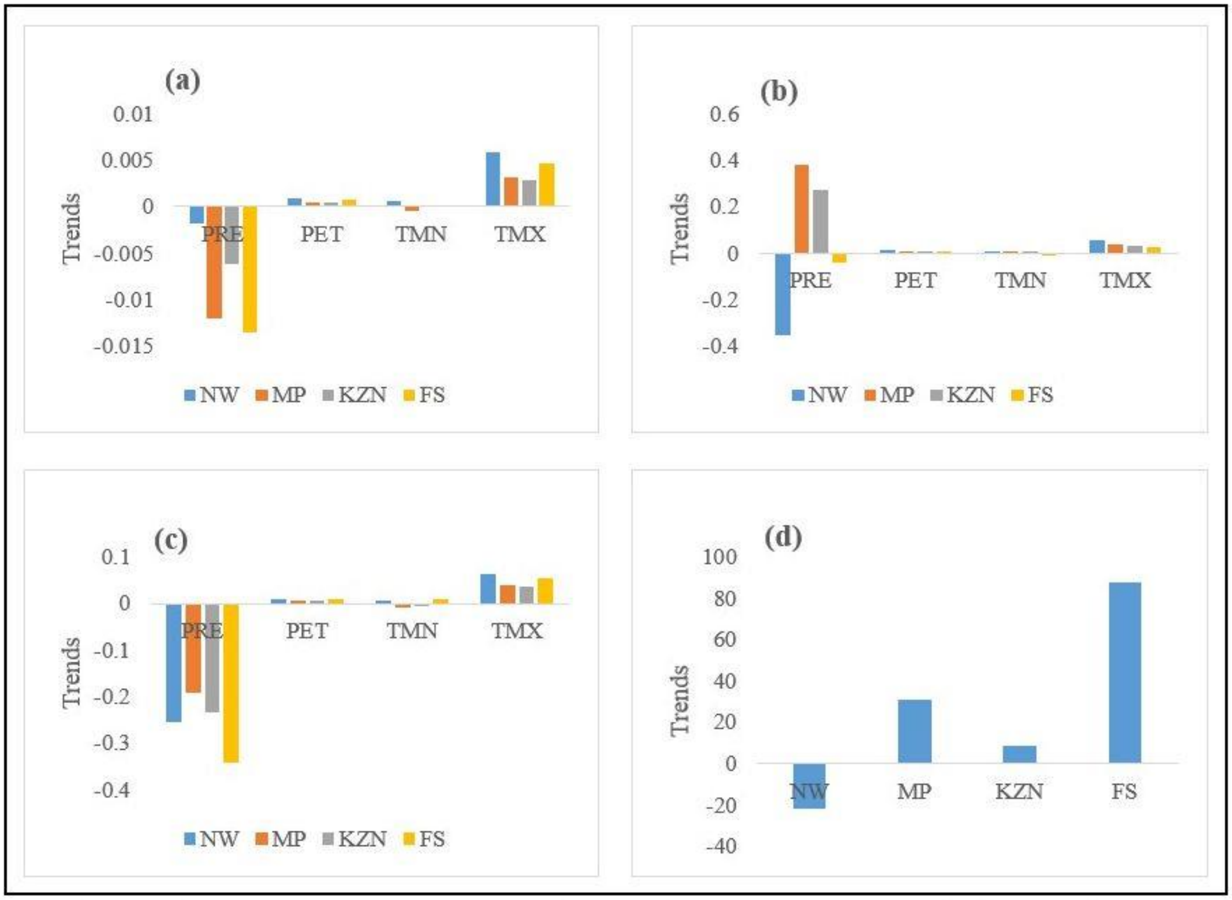

Figure 3-4: Trends of Precipitation (mm/month), Potential evapotranspiration (mm/day), Minimum and Maximum Temperature (oC) (1986-2015) at (a) monthly, (b) seasonal (NDJFM), (c) annual time series and (d) annual maize production trend (tons/year)

Moreover, the result of the analysis as shown in Fig 4d, indicates that there is a decreasing trend in annual maize production in North West by 22 tons/year. However, an increasing trend in annual maize production of about 30.87 tons/year, 8.57 tons/year and 87.88 tons/year are observed in Mpumalanga, KwaZulu-Natal and Free State respectively over the study period.

Table 3 depicts the significant level of the agro-climatic parameters across different time scale for the 30 years of study. Based on the *p*-value in Table 3, for all the agro-climatic parameters there is no significant difference in the monthly values (since all the values are greater than 0.05) except for maximum temperature which has a notable difference in the parameters for all the provinces (North West 0.003, Mpumalanga 0.013, KwaZulu-Natal 0.018 and Free State 0.034). This means that the monthly values for all the agro-climatic parameters are similar except for maximum temperature whose values differs significantly.

Table 3-3: The significance of linear trends in agro-climatic parameters (Precipitation (PRE); Potential Evapotranspiration (PET); monthly average daily minimum temperature (TMN); monthly average daily maximum temperature (TMX)) across different time scales for South African provinces (North West (NW); Mpumalanga (MP); KwaZulu-Natal (KZN); Free State (FS) from 1986-2015)

Provinces	**Variables**	**Monthly**		**Seasonal (NDJFM)**		**Annual**	
		***p*-value**	**Sign.**	***p*-value**	**Sign.**	***p*-value**	**Sign.**
NW	PRE	0.45	No	0.35	No	0.25	No
	PET	0.11	No	0.03	Yes	0.0002	Yes
	TMN	0.78	No	0.40	No	0.57	No
	TMX	0.003	Yes	0.01	Yes	0.00001	Yes
	Maize					0.37	No
MP	PRE	0.45	No	0.59	No	0.54	No
	PET	0.16	No	0.28	No	0.02	Yes
	TMN	0.80	No	0.96	No	0.32	No
	TMX	0.01	Yes	0.04	Yes	0.002	Yes
	Maize					0.005	Yes
KZN	PRE	0.78	No	0.52	No	0.41	No
	PET	0.16	No	0.17	No	0.02	Yes
	TMN	0.92	No	0.87	No	0.89	No
	TMX	0.02	Yes	0.01	Yes	0.001	Yes
	Maize					0.0001	Yes
FS	PRE	0.27	No	0.94	No	0.18	No
	PET	0.24	No	0.29	No	0.03	Yes
	TMN	0.97	No	0.63	No	0.51	No
	TMX	0.03	Yes	0.16	No	0.003	Yes
	Maize					0.0057	Yes

On the seasonal scale, maximum temperature for all the provinces exhibited significant difference (North West (0.01), Mpumalanga (0.04), and KwaZulu-Natal (0.01)) except for Free State (0.16) which had no notable difference. Potential evapotranspiration differed significantly only in North West (0.03) while the other provinces had no significant difference. Precipitation and minimum temperature in all the provinces had no notable difference during the rainy season. There was variation in the annual maize production values in all the provinces (Mpumalanga 0.005, KwaZulu-Natal 0.0001 and Free State 0.0057) for the period of study, except North West which had no substantial difference in its maize production. This means that the maize production values are not the same for the period of study expect for North West which had similar values.

3.4.3. Seasonal Variability

In this section we aim to determine the relationship between maize production and climatic variables across different seasons. The results for this analysis are summarized in Table 4. As shown in Table 4, there is a strong relationship between maize production and agro-climatic parameters in North West (approximately 4 % of variance in maize production can be explained from potential evapotranspiration in the area, precipitation explains 1% while maximum temperature explains 0.72 % of the maize production) during December January (DJ) growing season.

For February March season there was strong relationship between maize production and agro-climatic parameters in Mpumalanga (approximately 17 % of potential evapotranspiration explained the variation in maize production in the area, precipitation explained 12 %, minimum temperature explained 2% and maximum temperature explained 24.7 % the variability in maize production).

Similarly, in KwaZulu-Natal Potential evapotranspiration explained approximately 12 % of the variation of maize production in the province, precipitation explained 4 %, minimum temperature explained 3 % and maximum temperature explained 23 % of the variation of the maize production in the province. For Free State, potential evapotranspiration and precipitation explained approximately 9 % of the variability in maize production, minimum temperature explained 5 % and maximum temperature explained 19 % of the variability in maize production.

Table 3-4: Influence of the Agro-climatic Parameters on Maize Yield across Seasons. Precipitation (PRE); Potential Evapotranspiration (PET); monthly average daily minimum temperature (TMN); monthly average daily maximum temperature (TMX); North West (NW); Mpumalanga (MP); KwaZulu-Natal (KZN); Free State (FS); December January (DJ); December January February (DJF); February March (FM); November December January February March (NDJFM)

Variables	**DJ**				**DJF**				**FM**				**NDJFM**			
	NW %	**MP %**	**KZN %**	**FS %**	**NW %**	**MP %**	**KZN %**	**FS %**	**NW %**	**MP %**	**KZN %**	**FS %**	**NW %**	**MP %**	**KZN %**	**FS %**
PET	4.4	5.6	3.7	1.0	1.3	16	10.8	2.3	0.0	17.4	12.3	9	0.8	14.7	7.5	7.6
PRE	1.2	3.5	0.2	0.5	0.1	6.7	0.0	0.0	0.2	11.5	3.7	8.8	0.5	8	0.0	0.7
TMN	0.2	0.5	2.8	0.2	2.2	0.5	0.7	1	11.5	1.6	3.3	5.1	5.3	0.9	0.3	0.0
TMX	0.7	13.3	14.8	2.1	0.2	20	19.5	6.5	0.0	24.7	23.2	18.6	0.0	24	22	12.2

3.4.4. Multivariate analysis

In this study, a multivariate regression model was used to assess the impact of climate change based on seasonal PRE, PET, TMN and TMX variables on maize production where land is held in constant variation with production. In particular, the linear relationship developed in this analysis was to determine the maize production change due to changes in the four climate variables during 1986 – 2015, using the seasonal values since maize is grown during this period in South Africa.

The relationships were derived based on Equation (8). The multivariate regression analysis results are summarized in Table 5. Based on the results presented in Table 5, the model is able to describe the predisposing factors for variations in the maize production ranging from 44.39 % (0.4439) in the KwaZulu-Natal province to only 7.79 % (0.0779) in North West. Additionally, the *p*-values indicate that the influence of climate on the production of maize is significant in potential evapotranspiration (0.04), minimum temperature (0.02) and maximum temperature (0.0005) for KwaZulu-Natal as well maximum temperature for Mpumalanga (0.02) as their p values are greater than the significant level ($p \geq 0.05$).

As shown in table 5, from 1986 to 2015 an estimated decrease in maize production of about 1480.94 tons was observed for North West province when the values of PET, PRE, TMN and TMX are at their average (that is when PET is 5.25 mm/day, PRE is 74.84 mm/month, TMN is 16.36 ^{o}C and TMX is 30.72 ^{o}C (Table 2)). However, one percent increase in potential evapotranspiration (which is the combination of the other parameter) lead to a decrease of about 852.32 tons in maize production. One percent increase in precipitation (rainfall intensity) lead to decrease in maize production by 3.76 tons. Also, one percent increase in minimum temperature lead to an increase in maize production by 420.86 tons. Likewise, one percent increase in maximum temperature lead to an increase in maize production by 58.07 tons. However, the agro-climatic parameters predicted 7.79 % of the maize production.

For Mpumalanga province an estimated decreased in maize production for about 3535.36 tons was observed when the average of the four agro-climatic parameters are considered (that is when PET is 3.81 mm/day, PRE is 130.42 mm/month, TMN is 14.02 ^{o}C and TMX is 25.25 ^{o}C). One percent increase in potential evapotranspiration (combination of the other agro-climatic parameter) lead to a decrease of about 1751.44 tons of maize and also one percent increase in precipitation (rainfall intensity) lead to an increase in maize production by 0.56 tons. Furthermore, one percent increase in minimum temperature lead to a decrease of about 436.04 tons of maize and maximum temperature lead to an increase in maize production by 726.65 tons. In general, agro-climatic parameters only predicted about 32.52% of the maize production in the province (Table 5).

Maize production in KwaZulu-Natal decreased by 2317.28 tons when the average of agro-climatic parameters (PET (3.88 mm/day), PRE (124.37 mm/month), TMN (15.88 ^{o}C) and TMX (26.74 ^{o}C)) are considered (Table 5). However, there is a decrease of 395.16 tons and 115.81 tons in maize production when potential evapotranspiration (combination of the other parameters) and minimum temperature are increased by one percent respectively. On the other hand, one percent increase in precipitation and maximum temperature lead to increase of about 1.50 tons and 220.06 tons respectively in maize production. Agro-climatic parameters predicted 44.39 % of maize production in the province.

Considering the average of the four agro-climatic parameters (PET (5.12 mm/day), PRE (81.01 mm/month), TMN (13.92 ^{o}C), TMX (28.63 ^{o}C)), a decrease of about 14498.24 tons is observed in Free State (Table 5). One percent increase in potential evapotranspiration and minimum temperature lead to a decrease of about 1989.49 tons and 531.10 tons of maize production respectively. For precipitation and maximum temperature one percent increase lead to an increase of about 18.55 tons and 1185.38 tons in maize production respectively. However, the four agro-climatic parameters only predicted 21.85 % of maize production for Free State.

Overall, Table 5 depicts that, minimum temperature had the most influence on maize production for the study period in North West since it had the least p-value (0.32). Maximum temperature however had a notable influence on maize production in Mpumalanga ($p < 0.05$). For KwaZulu-Natal, potential evapotranspiration, minimum temperature and maximum temperature are the most influencing parameters. The most influential agro-climatic parameter to maize production in Free State is maximum temperature as it had the lowest *p*-value.

Table 3-5: Coefficients of the model. Precipitation (PRE) in mm/month; Potential Evapotranspiration (PET) in mm/day; monthly average daily minimum temperature (TMN) in ^{o}C; monthly average daily maximum temperature (TMX) in ^{o}C; Maize tons; KwaZulu-Natal (KZN)

Province	Crop	Constant	PET (*p*-value)	PRE (*p*-value)	TMN (*p*-value)	TMX (*p*-value)	R^2
North West	Maize	-1517.41	-852.32 (0.58)	-3.76 (0.77)	420.86 (0.32)	58.07 (0.89)	7.79
Mpumalanga	Maize	-3535.36	-1751.44 (0.17)	0.56 (0.89)	-436.04 (0.12)	726.65 (0.02)	32.52
KZN	Maize	-2317.28	-395.16 (0.04)	1.50 (0.06)	-115.81 (0.02)	220.06 (0.0005)	44.39
Free State	Maize	-14498.24	-1989 (0.40)	18.55(0.23)	-531.10 (0.19)	1185.38 (0.06)	21.85

Regression models for predicting maize yield from a new set of the four agro-climatic parameters values from equation 8 and Table 5:

*NW: Y = -1517.41 + (-3.76*PRE) + (-852.32*PET) + (420.86*TMN) + (58.07*TMX)*

*MP: Y = -3535.36 + (0.56*PRE) + (-1751.44*PET) + (-436.04*TMN) + (726.65*TMX)*

*KZN: Y = -2317.28 + (1.50*PRE) + (-395.16*PET) + (-115.81*TMN) + (220.06*TMX)*

*FS: Y = -14498.24 + (18.55*PRE) + (-1989*PET) + (-531.10*TMN) + (1185.38*TMX)*

3.5. Discussion

Maize is the most important grain crop grown in South Africa, despite the fact that South Africa is largely arid and semi-arid. However, the success in South Africa maize production depends on various factors, including weather and climate conditions. This study investigated the impact of PRE, PET, TMN and TMX climate variables on maize production in the North West, Free State, KwaZulu-Natal and Mpumalanga provinces, South Africa. The land cultivated for maize production during 2002-2015 was on average of about 1,036,000ha in Free State, 748,000ha in North West, 484,000ha in Mpumalanga and about 82,000ha in KwaZulu-Natal. Generally, the total provincial maize yield from KwaZulu-Natal was low, mainly due to the smaller land used for maize cultivation compared to the other provinces, most of the cultivated land in this province is under sugarcane production. Nonetheless, the maize yield per given unit land size was highest in KwaZulu-Natal due to favourable climate for maize production. On the other hand, the highest provincial maize yield was harvested from Free State due to the largest land used for the production of maize but the yield per unit area was the smallest among the provinces (Table 2).

Areas in the same climatic zone had similar agro-climatic parameters, except for maximum temperature in North West for the study period (1986-2015) which is different from that of Free State even though they are both in the same climatic zone (Table 2 and Fig 2). A noticeable disparity in the variation of the agro-climatic parameters among all the provinces is evident. For instance precipitation in Mpumalanga varies more than the other provinces, while the North West exhibits the greatest variability in potential evapotranspiration and maximum temperature. And the minimum temperature in Free State varied more than the other provinces. In case of maize production there is dissimilarity in the variation pattern within and among the provinces. The high variation in precipitation (Table 2) which happen to be the most influencing agro-climatic parameter in North West (Table 5) coupled with the high fluctuation in maximum temperature which went as high as 35 ^{o}C for some months could have contributed to the reduction in maize yield (negative trend, Fig 4d).

The recent drought that affected numerous sectors in the country is more evident across the study area, with most of these regions depicting a decrease in precipitation and an increase in potential evapotranspiration and maximum temperature (Fig 4), which is detrimental to crop production. The increase in the annual potential evapotranspiration and maximum temperature value is notable in all the provinces. The increase in the monthly potential evapotranspiration is subtle while there was significant increase in the monthly maximum temperature for all the provinces. The seasonal values showed notable increase in the potential evapotranspiration of North West and maximum temperature for all the provinces except Free State which had no significant increase in the maximum temperature.

From Table 4 the most significant season that impacts maize production differs from province to province. For instance, DJ favours maize production in North West province more than the other seasons. This could be attributed to the peak precipitation that is received during this season. This is also the planting season or germination stage when maize requires a warm and moist conditions for seedlings to emerge quickly (Jean 2003). For the other province (that is Mpumalanga, KwaZulu-Natal and Free State) however, FM months are more crucial to maize production. In order to enhance productivity farmers should regulate their planting time.

It is however important to note that aside from the agro-climatic parameters other factors which influence maize production in the provinces include land available for production, farm management decisions, government decision, topography, soil type and so on. From the time series analysis of production plotted against cultivated land (Fig 3), it can be deduced that production increases with increasing cultivated or available land and vice versa.

In North West and Free State provinces the agro-climatic parameters contribute about 7.79 % and 21.85 % respectively to maize production whereas in Mpumalanga and KwaZulu-Natal, the agro-climatic parameters contribute 32.52 % and 44.39 % of maize production. For North West, the minimum temperature has more influence on the maize production than the other agro-climatic parameters (Table 5), manipulating time of planting will help reduce the effect of minimum temperature on the maize production. In the case of Mpumalanga and Free State, maximum temperature has more influence on maize production than the other parameters. For KwaZulu-Natal (humid-subtropical) PET which is the combination of the other agro-climatic parameters, minimum temperature and maximum temperature influences maize production. The use of conservation agriculture and high yielding maize varieties will benefit the farmers to increase maize production. In Free State province, the maximum temperature is found to influence maize the most. Identifying drought tolerant maize varieties will improve adaptive capacity of the farmers in the province. We can conclude that maximum and minimum temperature influences maize production positively in all the provinces. But for KwaZulu-Natal more than one agro-climatic parameter influences maize production and the other two parameter (that is PET and TMN) which significantly influence maize production in the province had a negatively influence.

3.6. Conclusions

Many of the previous studies on the impact of climate change on crop production in South Africa have utilized methodologies such as crop processing, statistical and econometric models. Thus far, the body of literature focusing on determining a suite of agro-climatic parameters influencing maize production has largely remained in-exhaustive. This study contributes to this vital topic through investigating the most dominant climatic variables that influence maize yield in four provinces of South Africa. It is evident from this study that in the context of global change, increase in temperature leads to higher rate of evapotranspiration. On the other hand, decrease in precipitation leads to prolonged drought conditions which impact negatively on maize production. According to the South African Weather Service, there had been approximately 8 summer-rainfall seasons which had been 80 % less than normal in South Africa between July 1960 and June 2004. To combat this, farmers in Mpumalanga and KwaZulu-Natal could practise conservation agriculture whereby mechanical disturbance of soil is reduce and suitable variety of crops are grown. Furthermore, farmers in humid-subtropical areas of KwaZulu-Natal and Mpumalanga should get involved more in maize production since these areas favour maize yield per hectare more compared to the semi-arid areas (that is Free and North West). Additionally, identification of suitable maize varieties that tolerate frost for North West and drought and heat wave for Free State can be of great help. A limitation to this study is the non-availability of data on the cultivated land size covering the same time span of other data sets. This would have helped in making a time series comparison with maize yield and agro-climatic variables. However, the land data (2002-2015) indicated that there is strong similarity between cultivated land and production. This can be taken to be true for the previous years where data was not available. Finally, further studies are recommended to investigate the influence of other non-climatic factors such as farmers' decision-making process, who may or not have been informed due to access to information on climate change among other factors.

Acknowledgement

I will like to acknowledge the University of Pretoria through the Animal change project and DST for providing bursary through a grant that was received by University of Pretoria.

Conflicts of Interest

The authors declare no conflict of interest.

References

Ajadi BS, Adeniyi A, Afolabi MT (2011) Impact of climate on urban agriculture: case study of Ilorin City, Nigeria. GJHSS 11(1):45-49.

Botai CM, Botai JO, Dlamini LC, Zwane NS, Phaduli E (2016) Characteristics of Droughts in South Africa: A Case Study of Free State and North West Provinces. Water 8(10), 439; doi:10.3390/w8100439

Chipanshi AC, Chana R, Totolo O (2003) Vulnerability assessment of the maize and sorghum crops to climate change in Botswana. Climatic Change 61(3): 339–3360.

Department of Agriculture, Forestry and Fisheries Republic of South Africa (2012**)** Abstract of agricultural statistics. .

Department of Agriculture, Forestry and Fisheries Republic of South Africa (2015) Animal feeds market analysis report.

Deressa T, Hassan R, Poonyth D (2005) Measuring economic impact of climate change on South African‟s Sugarcane. Agrekon 44(4): 524-542.

Du Toit AS, Prinsloo MA, Durand W, Kiker G (2001) Report on vulnerability of maize production to climate change and adaptation assessment in South Africa. Agricultural Research Council, Grain Crops Institute.

Durand W (2006) Assessing the impact of climate change on crop water use in South Africa. CEEPA Discussion Paper #28. University of Pretoria, South Africa.

Erasmus B, Van Jaarsveld A, Van Zyl J, Vink N (2000) The effect of climate change on farm sector in the Western Cape. Agrekon 39(4):559-573.

FAO. Food and Agricultural Organization of the United Nation (2013) Effective rainfall in irrigated agriculture.

Fischer G, Mahendra S, Francesco NT, Harrij van V (2005) Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080. Phil. Trans R Soc B 360: 2067–2083 doi:10.1098/rstb.2005.1744.

Gbetibouo G, Hassan R (2005) Measuring the economic impact of climate change on major South African field crops: a Ricardian approach. Global and Planetary Change 47 (2–4): 143–152.

Harris I, Jones PD, Osborn TJ, Lister DH (2014) Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. International Journal of Climatology 34: 623-642

Hatfield JL, Boote KJ, Fay P, Hahn L, Izaurralde RC, Kimball BA, Mader T, Morgan J, Ort D, Polley W, Thomson A, Wolfe D (2008) Agriculture in:. The effects of climate change on agriculture, land resources, water resources, and biodiversity in the United States.

Hatfield JL, Boote KJ, Kimball BA, Ziska LH, Izaurralde RC, Ort D, Thomson AM, Wolfe DW, (2011) Climate impacts on agriculture: implications for crop production. Agron. J 103: 351–370.

Hawkins RH (1981) Interpretations of Source Area Variability in Rainfall-Runoff Relations. In International Symposium on Rainfall-Runoff Modeling; Water Resources Publications: Littleton, CO, USA, pp. 303–324.

Hewitson B (1999) Regional climate scenarios. Prepared for the SA Country Studies Programme, South Africa.

IPCC. Intergovernmental Panel on Climate Change (2007) Fourth assessment report, working group 2: Impacts, adaptation and vulnerability. Cambridge University Press, Cambridge Chapter 9.

James B, Liza U and James A (2009) Agriculture production's sensitivity to changes in climate in South Africa. South African Journal of Science 105.

Jean du P (2003) Maize Production. Compiled by Directorate Agricultural Information Services Department of Agriculture in cooperation with ARC-Grain Crops Institute. Printed and published by the Department of Agriculture and obtainable from Resource Centre Directorate Agricultural Information Services Private Bag X144, Pretoria, 0001 South Africa.

Jill E, Cairns, Jon H, Kai S, José LA, John FM , Christian T, Prasanna B M (2013) Adapting maize production to climate change in sub-Saharan Africa. Food Sec 5:345–360 doi: 10.1007/s12571-013-0256-x

Kottek M, Grieser J, Beck C, Rudolf B, Rubel F (2006) World map of Köppen Geiger climate classification updated. Meteorol Z 15: 259-263.

Kruger AC, and Shongwe S (2004) Temperature trends in South Africa: 1960–2003. International Journal of Climatology 24(15): 1929–1945.

Marchetto A, Rogora M, Arisci S (2013) Trend analysis of atmospheric deposition data: a comparison of statistical approaches. Atmospheric Environment 64: 95--102

Magadza CHD. (2000) Climate change impacts and human settlements in Africa: prospects for adaptation. Environ Monit Assess 61:193–205.

Molua EL, Benhin J, Kabubo MJ, Ouedraogo M, El-Marsafawy S (2010) Global climate change and vulnerability of African agriculture: implications for resilience and sustained productive capacity. Quarterly Journal of International Agriculture 49(3):183-211.

Molua EL, Lambi CM (2006) Assessing the impact of climate on crop water use and crop water productivity: The CROPWAT analysis of three districts in Cameroon. Centre for Environmental Economics and Policy in Africa, University of Pretoria #33.

Schulze RE, Kiker GA, Kunz RP (1993) Global climate change and agricultural productivity in southern Africa. Global Environmental Change 3(4): 330-349.

Suresh S and Indrajeet C (2017) Surface and Subsurface Transport of Nitrate Loss from the Selected Bioenergy Crop Fields: Systematic Review, Analysis and Future Directions. Agriculture 7, 27; doi:10.3390/agriculture7030027. www.mdpi.com/journal/agriculture

Tesfamariam EH, Annandale JG, Steyn JM, (2010) Water stress effects on winter canola growth and yield. Agron. J. 102:658-666.

Tesfamariam EH, Annandale JG, Steyn JM, Stirzaker RJ, Mbakwe I, (2015) Use of the SWB-Sci model for nitrogen management in sludge-amended land. Ag Water manage. 152:262-276.

Thornton PK, Jones PG, Ericksen PJ, Challinor AJ (2011) Agriculture and food systems in sub-Saharan Africa in a four-plus degree world. Philosophical Transactions of the Royal Society Series A 369:117–136.

Wenbin M, Fuliang Y, Chuanzhe L, Yuebo X, Jiyang T, Jia L, and Nana Z (2015) Effects of Rainfall Intensity and Slope Gradient on Runoff and Soil Moisture Content on Different Growing Stages of Spring Maize. Water 7: 2990-3008; doi:10.3390/w7062990

Wisdom A, Rashid MH, Claudia R (2008) Climate variability and maize yield in South Africa. Center for Environmental Economics and Policy in Africa and International Food Policy Research Institute. 28

Yinhong K, Shahbaz K, Xiaoyi M (2009) Climate change impacts on crop yield, crop water productivity and food security – A review. Progress in Natural Science 19 (2009) 1665–1674.

Chapter 4

CHANGES IN THE SATELLITE DERIVED PHENOLOGICAL PARAMETERS AND ITS RELATIONSHIP WITH MAIZE PRODUCTION

Variability of satellite derived phenological parameters across maize producing areas of South Africa

***Omolola M. Adisa* [1,*]**, Joel O. Botai [1,2], Abubeker Hassen [3], Daniel Darkey [1], Abiodun M. Adeola [2], Eyob Tesfamariam [4], Christina M. Botai [2], Abidemi T. Adisa [5]

[1]Department of Geography, Geoinformatics & Meteorology, University of Pretoria, Private Bag X20, Hatfield, Pretoria 0028, South Africa; lolaadisa@yahoo.com (O.M.A.); daniel.darkey@up.ac.za (D.D.)

[2] South African Weather Service, Private Bag X097, Pretoria 0001, South Africa; joel.botai@weathersa.co.za (J.O.B.); abiodun.adeola@weathersa.co.za (AMA); christina.botai@weathersa.co.za (C.M.B.)

[3] Department of Animal and Wildlife Sciences, University of Pretoria, Private Bag X20, Hatfield, Pretoria 0028, South Africa; abubeker.hassen@up.ac.za (A.H.)

[4] Department of Plant and soil Sciences, University of Pretoria, Private Bag X20, Hatfield, Pretoria 0028, South Africa; eyob.tesfamariam@up.ac.za (E.T.)

[5]Department of Agricultural and Applied Economics, Texas Tech University, Lubbock Texas, USA; abidemi.adisa@ttu.edu (A.T.A.)

* Corresponding author. u13387562@tuks.co.za; Tel.: +27 84 849 1170

Received: 21 June 2018; Accepted: 31 July 2018; Published: date

This article has been published in Sustainability, https://www.mdpi.com/2071-1050/10/9/3033

Abstract:

Changes in phenology can be used as a proxy to elucidate the short and long term trends in climate change and variability. Such phenological changes are driven by weather and climate as well as environmental and ecological factors. Climate change affects plant phenology largely during the vegetative and reproductive stages. The focus of the study was to investigate the changes in phenological parameters of maize as well as to assess their causal factors across the selected maize producing Provinces (viz: North West, Free State, Mpumalanga and KwaZulu-Natal) of South Africa. For this purpose, five phenological parameters i.e. the length of season (LOS), start of season (SOS), end of season (EOS), position of peak value (POP), and position of trough value (POT) derived from the MODIS NDVI data (MOD13Q1) were analysed. In addition, climatic variables (Potential Evapotranspiration (PET), Precipitation (PRE), Maximum (TMX) and Minimum (TMN) Temperatures spanning from 2000 to 2015 were also analysed. Based on the results, the maize producing Provinces considered exhibit a decreasing trend in NDVI values. The results further show that Mpumalanga and Free State Provinces have SOS and EOS in December and April respectively. In terms of the LOS, KwaZulu-Natal Province had the highest days (194) followed by Mpumalanga with 177 days while North West and Free State Provinces had 149 and 148 days respectively. Our results further demonstrate that the influences of climate variables on phenological parameters exhibit a strong space-time and common covariate dependence. For instance, TMN dominated in North West and Free State, PET and TMX are the main dominant factors in KwaZulu-Natal Province whereas PRE highly dominated in Mpumalanga. Furthermore, the result of the Partial Least Square Path Modeling (PLS-PM) analysis indicates that climatic variables predict about 46% of the variability of phenology indicators and about 63% of the variability of yield indicators for the entire study area. The goodness of fit index indicates that the model has a prediction power of 75% over the entire study area. This study contributes towards enhancing the knowledge of the dynamics in the phenological parameters and the results can assist farmers to make the necessary adjustment in order to have an optimal production and thereby enhance food security for both human and livestock.

Keywords: Phenology; Maize; MODIS; NDVI; Climate; Variation

4.0. Introduction

Phenology studies the seasons and cycle of natural phenomena controlled by both climatic and environmental factors [1]. It determines the duration and time taken by plant canopy to be photosynthetically active and equally drives the annual uptake of carbon in an ecosystem [2,3]. It also indicates long-term trends in climate as well as short-term climatic variation as it is driven by; precipitation, photoperiod and temperature [4]. Climate change occurs at both global and regional level and it significantly affects vegetation dynamics through the increasing global mean temperature and change in the precipitation regimes [5]. Consequently, climate change affects the plant phenology due to its influence on the flowering time and the other plant developmental stages [6]. The changes in vegetation phenology in the past decades, detected from both ground observation and satellite remote sensing phenological methods has drastically drawn the attention of scientific community to plant phenology [7,8].

Although first-hand phenology information are assessed with the ground observation phenological methods [9] but the major hitch of these methods, is that they are localized, lacking global coverage, covering limited number of species and highly labour intensive [10]. However, modern remote sensing techniques provides a promising option and new opportunities for phenological studies [11], since it allows the usage of global coverage data at various spatial and temporal scales, making it easy to study phenology and its drivers. Phenological products have been proven to be useful and it has been applied in many fields, like biomass monitoring [12,13], farm management [14,15], and climate change [16-20]. In the past two decades, the usage of satellite to determine the vegetation phenology has been an active area of research [8]. Evident in the numerous studies at local and global scales, arrays of algorithms and techniques that handle wide-ranging spatial resolution and temporally discontinuous satellite data have emerged [20]. Remotely sensed vegetation phenological metrics such as Vegetation Indexes (VIs) are derived from satellite time-series data of vegetation parameters. The VIs are among the mostly used parameters and these comprise of the Enhanced Vegetation Index (EVI) [21-22] and the Normalized Difference Vegetation Index (NDVI) [23]. Some other vegetation indices that indicate the growing season changes explored in many studies include; Meris Terrestrial Chlorophyll Index (MTCI) [24], Wide Dynamic Range Vegetation Index (WDRVI) [25], Perpendicular Vegetation Index (PVI) [23] and Soil Adjusted Vegetation Index (SAVI) [26].

NDVI is the measurement of vegetation greenness using the remote sensing technique, it is associated to the plant's structural properties such as the green biomass [27] as well as the leaf area index [28] and also relates to properties of vegetation productivity that is the absorbed foliar nitrogen and the absorbed photosynthetic active radiation [29]. As reported by Reference [30], the physiological response of crops to environment conditions as well as their biophysical characteristics does change seasonally as vegetation grows. Information on the phenological stage of a crop is essential for understanding the seasonal exchange of ecosystem carbon dioxide (CO_2), fertilizer management, evaluating crop productivity and irrigation scheduling. Maize is the focus of this study and it is a major livestock feed and stable food in South Africa. The reproductive stage which is from the sulking to physiological maturity (degree of kernel development) and the vegetative stage which is from emergence to tasselling (number of fully expanded leaves), requires optimal supply of nutrient under favourable environmental conditions (that is solar radiation, precipitation, soil moisture, temperature), for maximum yield [31,32]. Previous studies [33,34,35] have shown that sustainable development in Southern Africa is threatened by extreme conditions such as water availability (precipitation), rise in air temperature as well as shortening of the length of growing season. Also records show that agricultural production in 2015/16 as reduced by 1.6% compared to that of 2014/15 [34], also there is reduction in the field crop volume by 12.7%, resulting in reduction of winter crop production (canola and wheat), summer crops (sorghum and maize), sugar cane and oilseed crops (groundnuts and soya beans) [36].

The analysis of the variability of the phenological parameters induced by climate change and variability can allow for more accurate prediction of the timing of planting crops and help improve managerial decisions, through the provision of phenological parameters (such as; start of season (SOS), end of season (EOS), length of the season (LOS), maximum NDVI during the season. This study aims at investigating the changes in the phenology metrics in and the associated changes in maize yield and the potential causal factors across the four major producing Provinces of South Africa, namely North West (NW), Free State (FS), Mpumalanga (MP) and KwaZulu-Natal (KZN). The specific objectives of the study are, a) to calculate the temporal trends of thephenological parameters, b) to assess the possible association of the changes in phenological parameters with changes in maize yield, and c) to identify the most significant drivers of such phenological parameters-maize yield changes.

4.1. Materials and Method

4.1.1. Study Area

The study area covers the north-eastern part of South Africa between longitude 22^{o}E to 33^{o}E and latitude -32^{o}S to -24^{o}S. The region covers KwaZulu-Natal, Free State, Mpumalanga and North West Provinces, see Figure 1. These Provinces account for approximately 83% of the total maize production for South Africa. FS and NW Provinces together contribute to more than 60% of the total maize produced in the country, followed by MP (~24%) and KZN (less than 5%). Free State is about 1,300m above sea level and is characterized by a hot and arid climate. This Province is characterized by chilly winters (ranging from a cold 1^{o}C to mild 17^{o}C), plenty of sunshine (15^{o}C to 32^{o}C) and summer rains (500 mm-600 mm annually). Located in the northern part of the country, is the Vaal irrigated area which nourishes the small assortment of farming towns. In NW Province there is almost a year-round sunshine, with an average rainfall of 300 to 700 mm annually. The summer temperature ranges from 22^{o}C to 34^{o}C. The NW Province is characterized by dry, sunny days and chilly nights during winter (2^{o}C to 20^{o}C). The temperature in KZN ranges between 23^{o}C to 33^{o}C in summer (i.e. September - April), and 16^{o}C to 25^{o}C during winter. The Province is characterized by long, hot summers with average annual rainfall ranging between 500 mm and 800 mm, and mild winters. Furthermore, the western part of MP Province is much colder during winter and hotter during summer than the other parts of the Province. The average annual temperature is about 19^{o}C and rainfall is between 500 mm and 800 mm annually.

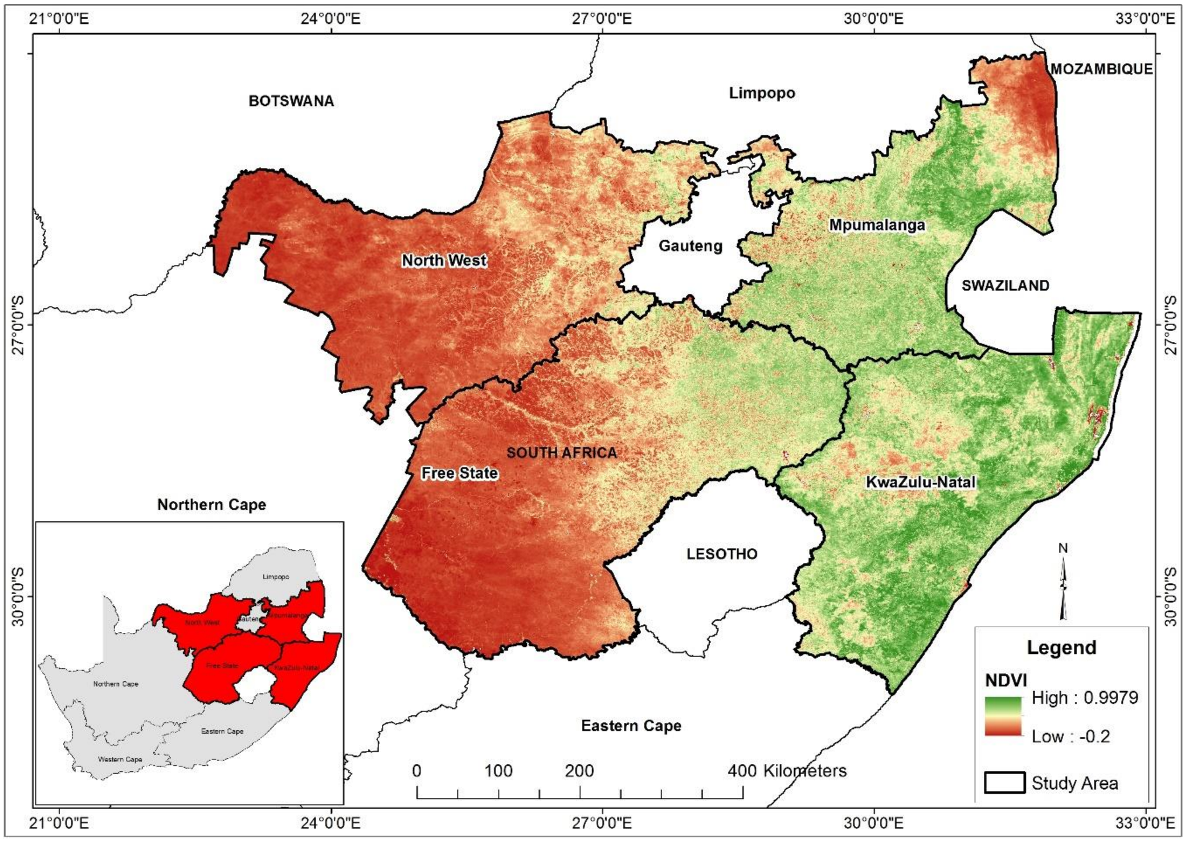

Figure 4-1: The Map of major maize producing Provinces of South Africa showing the Normalised Difference Vegetation Index (NDVI) for 51st week of the year 2016. NDVI values range from -1 to +1 indicating the response of vegetation to water availability. With high values tending towards 1 meaning healthy vegetation and lower values meaning barren, built land and negative as water surface

4.1.2. Materials

A 16-day NDVI composite from MODIS (MOD13Q1) data on board the TERRA and AQUA satellites, with spatial resolution of 250 m, was acquired from Land Processes Distributed Active Archive Centre (LP DAAC) located at United States Geological Survey (USGS) Earth Resource Observation and Science (EROS) centre for the period of 2000 to 2015. This data is designed in such a way that a variety of information ranging from oceanic conditions to atmospheric and land conditions can be retrieved from it. MOD13Q1 is one of the 44 products (that is processed data) developed by the MODIS science team using a large number of spectral bands.

Maize production data sets in tonnes (tons) for the major maize producing Provinces spanning from 2000 to 2015 were obtained from the Abstract of Agricultural Statistics compiled by the Department of Agriculture, Forestry and Fisheries of South Africa. This abstract document contains important information on *inter alia*, field crops, horticulture, livestock, vital indicators, total land area in hectares (ha) cultivated for maize production and the contribution of primary agriculture to the South African economy. The analysed data are available on the department's website, www.daff.gov.za.

Gridded climate dataset, of the Climate Research Unit Time-Series 3.24.01 (CRU TS 3.24.01) spanning the period 1986–2015 was used in this study. The CRU TS climate data sets are derived from monthly observations from more than 4000 meteorological stations distributed across the world's land areas. The gridded CRU TS 3.24.01 product is freely available for science community on http://www.cru.uea.ac.uk or http://badc.nerc.ac.uk/data/cru. For more information on the construction of the CRU TS 3.24.01 product, the reader is referred to Reference [37]. For the purpose of this study, four climatic variables i.e., precipitation (PRE), maximum and minimum temperature, (TMX) and (TMN) and potential evapotranspiration (PET) spanning the period of 2000-2015 were analyzed. The PET was calculated based on the Penman-Monteith formula reported in [38].

4.1.3. Methods

MODIStsp, a new "R" package that allows generation of time series of rasters automatically from Land Products data derived from MODIS satellite data was used to acquire the MODIS NDVI (MOD13Q1) data [39]. The NDVI was derived from spectral measurement of the MODIS sensor using Equation (1).

$$\mathbf{NDVI} = \frac{(\mathbf{NIR-Red})}{(\mathbf{NIR+Red})} \tag{1}$$

In Equation (1), NIR represents the near-infrared regions while Red represents the spectral reflectance measurements required in the red (visible). The NDVI varies between -1.0 and +1.0. The MOD13Q1 data are provided every 16 days at 250-meter spatial resolution as a gridded level-3 product in the Sinusoidal projection. The spatial extent was set by uploading the spatial file for South Africa so as to extract the data for South Africa and thereafter extract the NDVI data for the four major maize producing Provinces. A comprehensive procedure of downloading and extracting the MODIS data is described in Reference [39].

The output were processed using the greenbrown package in R software version 2.2 [40] to calculate the phenology metrics on time series from which the start of season (SOS), end of season

(EOS), length of season (LOS), position of peak (POP), position of trough (POT), spanning from 2000 to 2015. The phenological parameters analysed in this study are summarised in the Table 1.

Table 4-1: Description of the phenological parameters

Phenological metrics	Acronym	Phenological Interpretation	Description
Start of Season	SOS	Beginning of measurable photosynthesis in the vegetation canopy	Day of year identified as having a consistent upward trend in time series NDVI
End of Season	EOS	End of measurable photosynthesis in the vegetation canopy	Day of year identified at the end of a consistent downward trend in time series NDVI
Length of Season	LOS	Length of photosynthetic activity (the growing season)	Number of days from the SOS and EOS
Position of the Peak (maximum)	POP	Time of maximum photosynthesis in the canopy	Day of year corresponding to the maximum NDVI in an annual time series
Position of trough (minimum)	POT	Time of minimum photosynthesis in the canopy	Day of year corresponding to the minimum NDVI in an annual time series

The statistical characteristics of the NDVI and derived phenological parameters were calculated for the purpose of obtaining statistical description. The datasets were de-trended using the quadratic polynomial trend to remove fluctuations attributed to non-climatic factors. The Ordinary Least Square (OLS)-based MOSUM [41] test was used to detect the structural changes and the breakpoints in the time series of the datasets. Statistical significance was tested at 95% confidence limit.

In this contribution, we posit that changes in maize yield is linked to the changes in phenological parameters which are driven mainly by climatic factors among other factors. To test this hypothesis, the Partial Least Square Path Modeling (PLS-PM) was used [42]. Hence, we developed a model that consist of three latent variables; Climate $=LV_1$, Phenology $=LV_2$ and Yield $=LV_3$. Each latent variable is associated with at least 2 manifest variables TMN, TMX, PET and PRE for climate, SOS, EOS, LOS, POP and POT for phenology; and production and cultivated land for yield as shown in figure 2.

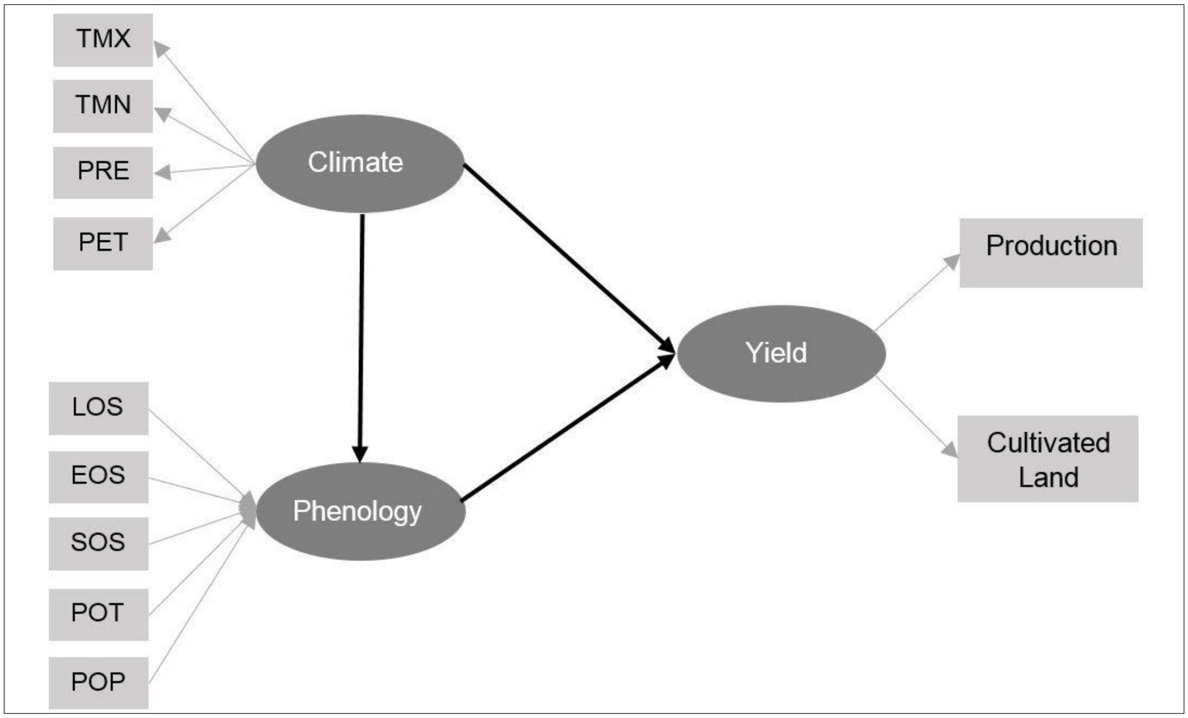

Figure 4-2: ***Path Diagram of the PLS model showing the inner model (Structural) between the three latent variables in dark grey oval shapes and the outer model (measurement) with their manifest variables***

The changes in the phenological variables can be considered as reflective indicators because they reflect the variation in climatic factors; considered as a formative indicator because they are thought to influence the quantity of Yield. Hence, $LV_{\mathbf{2}}$ and LV_3 are treated as reflective blocks expressed as

$$X_{2k} = \lambda_{2k} LV_2 + \varepsilon \qquad k = 1,2,3 \qquad (2)$$

$$X_{3k} = \lambda_{3k} LV_3 + \varepsilon \qquad k = 1,2,3 \qquad (3)$$

and LV_1 as formative block. $LV_1 = \sum_k \lambda_{jk} X_{1k} + \varepsilon \qquad k = 1,2,3 \qquad (4)$

where λ_{jk} are loadings; and ε is the error terms accounting for the residuals

Shown in figure 2 is the Path Diagram of the PLS model indicating the 2 sub-models; the inner and the outer model. The inner model has to do with the relationships between the latent variables and the outer model has to do with the relationships between each latent variable and its block of indicators. For the inner model, two equations were developed. The first is the one which LV_2 depends onLV_1:

$$LV_{2j} = \beta_{ji} LV_{1i} + \varepsilon_j \quad (5)$$

The second inner relationship is the one which LV_3 depends on LV_1 andLV_2:

$$LV_{3j} = \beta_{ji} LV_{1i} + \beta_{32ji} LV_{2i} + \varepsilon_j \quad (6)$$

where the subscript $\boldsymbol{i}$ of LV_i refers to all the latent variables that are supposed to predict LV_j. The coefficients β_{ji} are the path coefficients and they represent the "strength and direction" of the relations between the response LV_j and the predictorsLV_i. β_o is the intercept term, and $\boldsymbol{\varepsilon_j}$ **is** the error term accounting for the residuals. All variables were standardized.

In order to assess the outer model, the unidimensionality function was used. In this regard, the Cronbach's alpha, Dillon-Goldstein's rho, as well as first eigenvalue of the indicators' correlation matrix were computed. Additionally, the structural model was assessed by computing the R^2 determination coefficients, the redundancy index, and the Goodness-of-Fit (GoF).

4.2. Results

4.2.1. Summary statistics and trends in MODIS derived NDVI

NDVI statistical characteristics results for the period spanning 2000-2015, are depicted in Table 2. The highest maximum (0.71), minimum (0.35) and median (0.56) NDVI values were recorded in KZN Province while the lowest maximum (0.52), minimum (0.21) and median (0.31) NDVI values were recorded in the NW Province. The variation of NDVI values is high in FS (coefficient of variation; CV = 26.33), NW (CV = 25.93) and MP (CV = 25.55) Provinces and less in KZN (CV = 19.13). The trends of the NDVI time series (black), seasonally adjusted and fitted with the NDVI data (green) are illustrated in figure 2, while figure 3 depicts the spatial pattern of trends and *p*-values of the NDVI over the period of the study.

Table 4-2: ***Statistical summary of Normalized Difference Vegetation Index (NDVI) values across the selected Provinces (2000-2015) and maize yield (tons/hectare)***

Province	Variable	Minimum	Maximum	Median	Coefficient of Variation (CV)	*p*-*value*	Trend
Free State (FS)	NDVI	0.212	0.56	0.32	26.33	0.01	-0.00
	Maize Yield	2.80	5.20	3.95	19.01	0.38	0.04
Mpumalanga (MP)	NDVI	0.29	0.67	0.47	25.55	0.01	-0.00
	Maize Yield	3.20	6.40	5.10	19.06	0.15	0.11
	NDVI	0.21	0.52	0.31	25.93	0.01	-0.00

North West (NW)	Maize Yield	1.80	4.40	3.10	25.52	0.47	0.05
KwaZulu-Natal (KZN)	NDVI	0.35	0.71	0.56	19.13	0.01	-0.00
	Maize Yield	4.50	6.40	5.70	10.91	0.01	0.10

Generally, negative trends that are statistically significant at α = 5% (p-value = 0.01) were detected in the monthly NDVI values in all the four Provinces. As shown in figure 3, there were breakpoints in the time series in the month of July 2009 in the FS Province, January 2004 in Mpumalanga Province and July 2008 and June 2012 in North West and KZN Provinces, respectively.

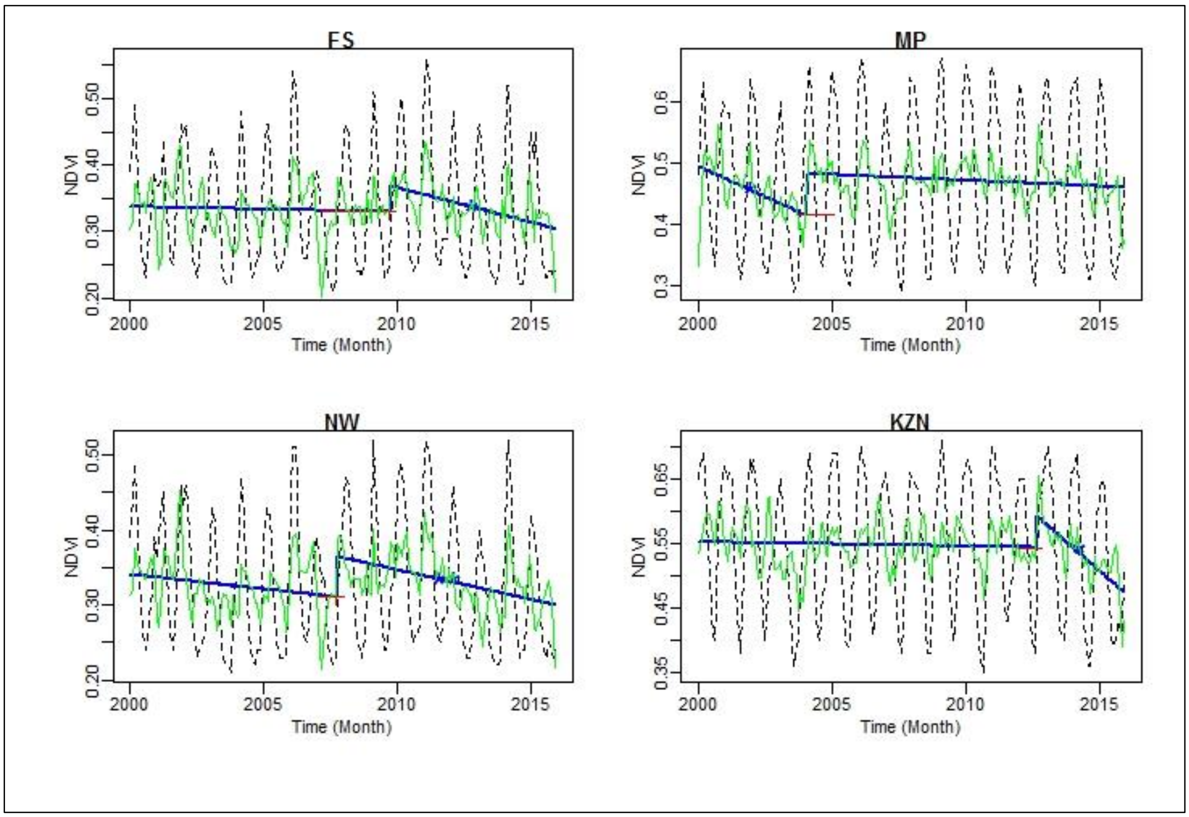

Figure 4-3: Plot of time series of NDVI (black lines) with NDVI trends (blue lines) fitted with seasonally adjusted NDVI (green lines) across the four major maize producing Provinces; FS: Free State, MP: Mpumalanga, NW: North West and KZN: KwaZulu-Natal

Positive trends (green) were detected in the north and central regions, towards the southern part of the study area consisting of district municipalities such as Nkangala, Gert Sibande in Mpumalanga Province, Fezile Dabi, Thabo Mofutsanyane and Lejweleptswa in Free State Province and in Umgungundlovu, Sisonke and Ugu in KwaZulu-Natal, see figure 4A. However, the observed trends are not statistically significant, see for instance figure 4B. On the other hand, negative trends in NDVI values were detected in the north-eastern parts of Ngaka Modiri Molema and north-western regions of Bojanala districts in the north-eastern parts of North West Province, north-eastern parts of Ehlanzeni in Mpumalanga Province as well as in the central; north-eastern parts of KwaZulu-Natal Province. The negative trends are statistically significant are shown in figure 4B.

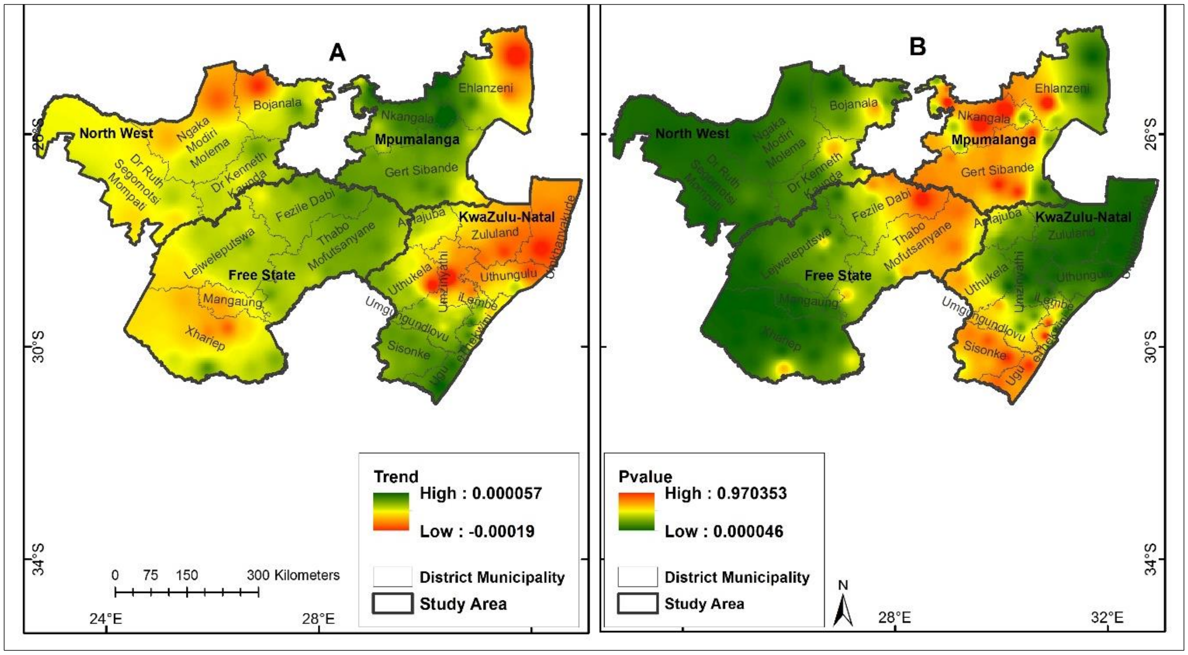

Figure 4-4: Spatial pattern of NDVI time series trends and p-value from 2000 to 2015 across major maize producing areas of South Africa

4.2.2. Statistical moments of phenological parameters

Figure 5 depicts the statistical characteristics of the phenological parameters across the study area. Based on the results, the SOS ranges between 260th and 359th day of the year, with a noticeable outlier in KZN. Over the 17-year period, the North West Province exhibited SOS median value of 336 day of the year which falls in December and ends (EOS) on 120 day of the following year (April), while the LOS median value is approximately 166 days. The NDVI peak value (position of peak value (maximum) (POP)) was attained on the 38 day of the year (i.e., around February) while the NDVI trough value (position of trough value (minimum) (POT)) was attained on the 225 day of the year, which is around August. The mean growing season NDVI (MGS) value for North West Province is 0.42. In Mpumalanga Province, the median SOS falls on 304 day of the year (corresponding to days in November), the median EOS is on 111 day of the following year (around April) while the median LOS is approximately at about 178 days. The peak NDVI value (POP) occurs around the 14th day of the year (around January) while the trough NDVI value (POT) is determined to be around the 215th day of the year (around August). The MGS value for Mpumalanga Province is 0.58. The growing season for KwaZulu-Natal Province starts on around the 293rd day of the year (October), and ends on the 126 day of the following year (May). The LOS stretches for about 196 days. The maximum NDVI value is detected on the 19th day of the year (January) while the minimum NDVI value occurs around the 203rd day of the year (July). The MGS value for KwaZulu-Natal is 0.63. In Free State, the season starts (SOS) on the 319th day of the year, which is in November, and ends (EOS) on the 114th day of the following year (April), the LOS stretches for about 151 days. The MGS value for this area is 0.42. The maximum NDVI value was detected on the 35th day of the year (around February) while the minimum NDVI value was on the 193rd day of the year (July).

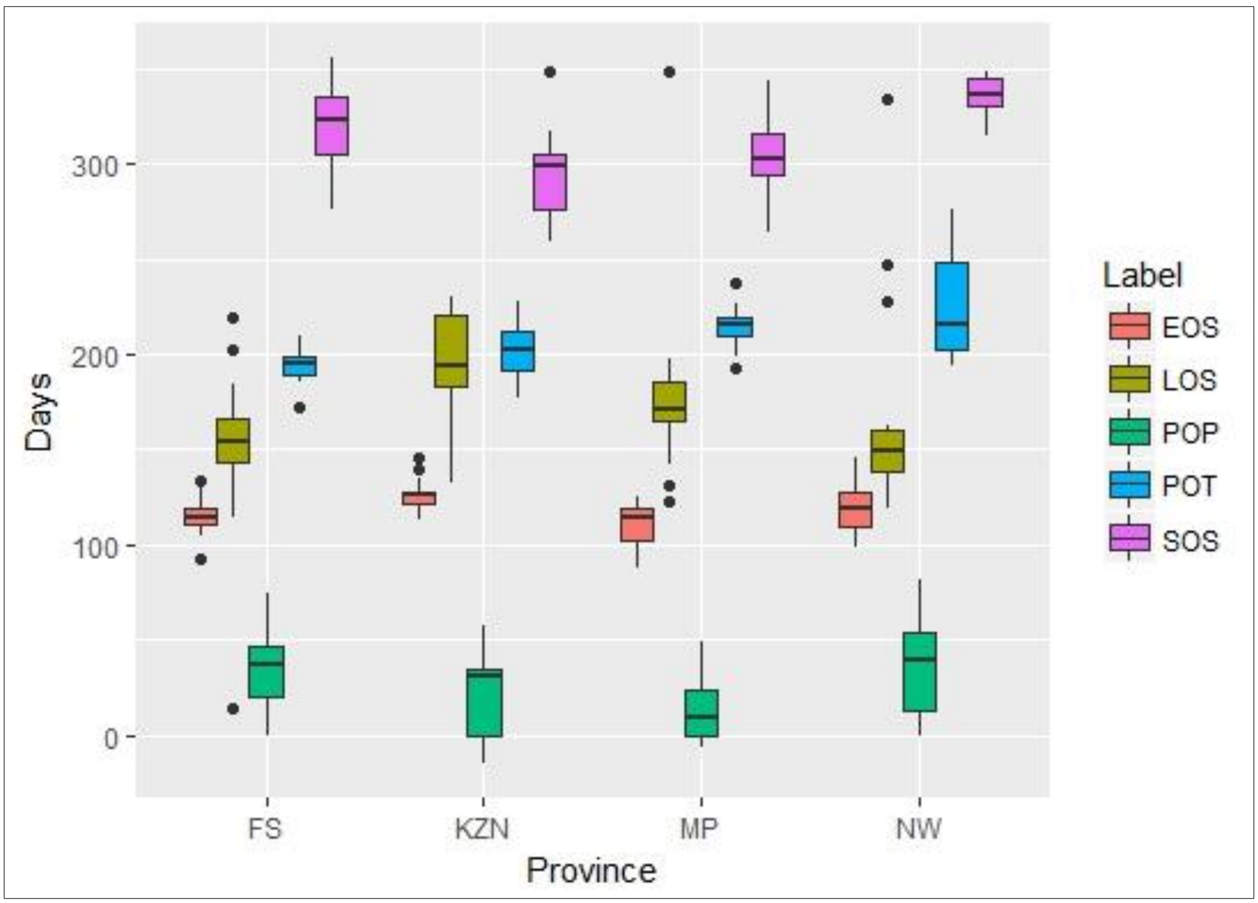

Figure 4-5: Distribution of Phenological Parameters across the major maize producing areas (2000-2016); Start of Season (SOS), End of Season (EOS), Length of Season (LOS), Position of Peak Value (POP) and Position of Trough Value (POT); Free State (FS), KwaZulu-Natal (KZN), Mpumalanga (MP) and North West (NW)

The graphical illustration of the phenological parameters is shown in figure 6. From this figure, it is evident that the planting season starts (SOS) late in the North West and Free State Provinces as compared to the other two provinces. The growing season for the KwaZulu-Natal and North West Provinces ends late (that is higher EOS values) as compared to other areas. However, the KwaZulu-Natal and Mpumalanga Provinces experienced the longest growing season (higher LOS values). The North West and Free State Provinces exhibited the highest POP values while the North West and Mpumalanga Provinces showed the highest POT values.

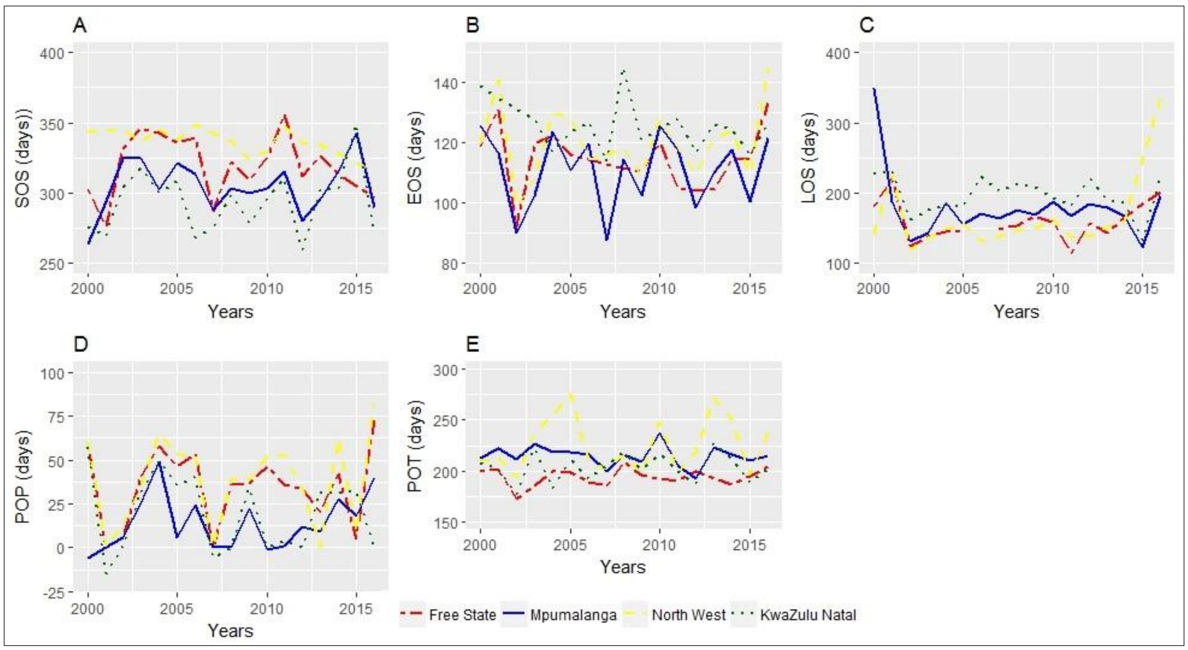

Figure 4-6: Time series of phenological parameters across major maize producing Provinces (2000-2015); (A) Start of Season (SOS), (B) End of Season (EOS), (C) Length of Season (LOS), (D) Position of Peak Value (POP) and (E) Position of Trough Value (POT); dashed red, dark blue, dashed yellow and dashed green lines represent Free State, Mpumalanga, North West and KwaZulu-Natal respectively

Figure 7 depicts results for the computed coefficient of variation (CV). The CV results indicate that the POP exhibited the greatest variability while SOS and POT exhibited the least variability, in all the major maize producing Provinces of South Africa. However, the POP in KwaZulu-Natal and Mpumalanga varies more than the other two Province. The LOS in KwaZulu-Natal had the least variation compared to the rest of the Provinces. And POT in North West varied more than the other Provinces.

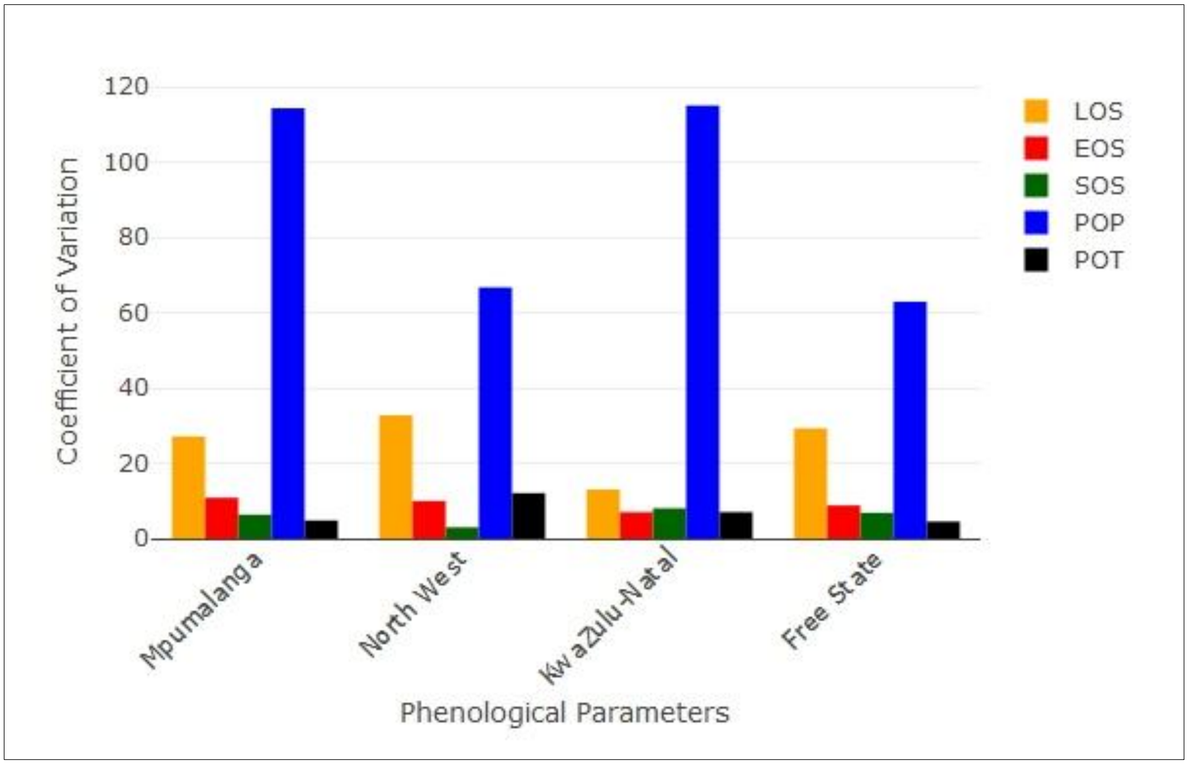

Figure 4-7: The coefficient of Variation (CV) among the Phenological Parameters (2000-2016); Start of Season (SOS) green, End of Season (EOS) red, Length of Season (LOS) orange, Position of Peak Value (POP) blue and Position of Trough Value (POT) black

4.2.3. Trends in the phenological parameters from 2000 to 2015

Shown in Figure 8 and Table 3 are the trend in the phenological parameters from 2000 to 2015 as well as the statistical significance of trends in the phenological parameters. Negative trends in the SOS were detected across the entire maize producing Provinces with exception to KwaZulu-Natal which depicted a positive trend. The SOS exhibited similar trend patterns across all but one (North West) Provinces. Furthermore, negative trends in EOS were observed across the study area, with exceptions to the North West Province which depicted a positive trend with no significant difference. The LOS exhibited a positive trend in all the Provinces except for KwaZulu-Natal Province, with no significant difference in the LOS for all the Provinces except for North West Province which increased significantly. The POT exhibited a positive trend in all but one (Mpumalanga) Province. On the other hand, POP in Free State and KwaZulu-Natal Provinces showed negative trend while POP in Mpumalanga and North West Provinces experienced positive trends. Trends in both POT and POP were found to be statistically insignificant across the Provinces.

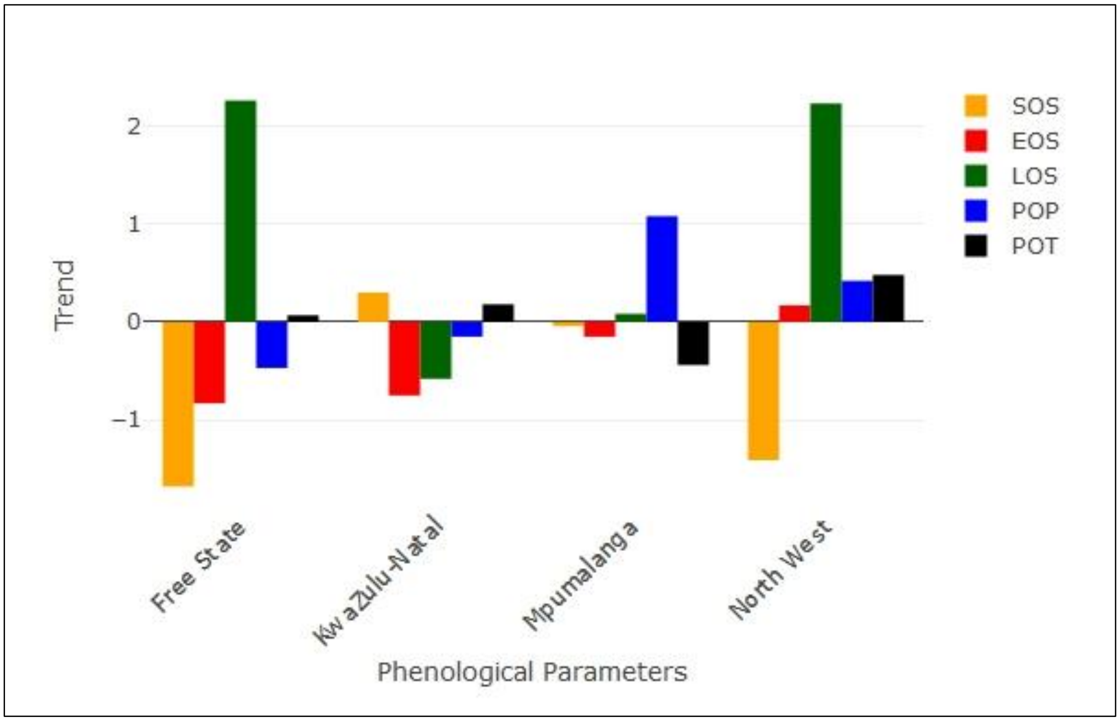

Figure 4-8: Trend in Phenological parameters (2000-2015). Start of Season (SOS) green, End of Season (EOS) red, Length of Season (LOS) orange, Position of Peak Value (POP) blue and Position of Trough Value (POT) black

Table 4-3: Statistical significance of trends in phenological parameter

Provinces	Variables	p-value	Significance	Trend
NW	SOS	0.003	Yes	-1.41
	EOS	0.68	No	0.17
	LOS	0.04	Yes	2.23
	POP	0.74	No	0.42
	POT	0.68	No	0.48
MP	SOS	1	No	-0.042
	EOS	0.87	No	-0.15
	LOS	1	No	0.083
	POP	0.15	No	1.08
	POT	0.34	No	-0.44
KZN	SOS	0.71	No	0.3
	EOS	0.09	No	-0.75
	LOS	0.71	No	-0.58
	POP	0.48	No	-0.15
	POT	0.93	No	0.18
FS	SOS	0.48	No	-1.68
	EOS	0.32	No	-0.83
	LOS	0.17	No	2.26
	POP	0.74	No	-0.47
	POT	0.97	No	0.068

4.2.4. Association of changes in maize yield and changes in phenological parameters

Considering the circle of correlations for Free State in Figure 9a, POT had the closest correlation with the maize yield. On the other hand, EOS, POP, LOS and SOS had a very strong correlation with each other, although LOS, POP and SOS were poorly represented in the plot while the other phenological parameter were well represented in the circle of correlations plot. This means that the LOS, SOS, EOS and POP for Free State had a very strong relationship. In the circle of correlations for KwaZulu-Natal (Figure 9b), POT also had the greatest influence on the maize yield for the area. However, there exist no correlation among the phenological parameters in the area. And EOS and POT were poorly represented in the plot while the other phenological parameters were well represented in the plot. For Mpumalanga Province (Figure 9c) POP and LOS had a very strong influence on the maize yield than the other phenological parameters. There is also a close relationship between LOS and POP, this means that these parameters influences each other, although POP has less influence as shown in Figure 9c. Maize yield in the North West Province is equally strongly influenced by POT according to the circle of correlations in Figure 9d. The LOS and the EOS in this Province had a very close relationship suggesting that they influence each other.

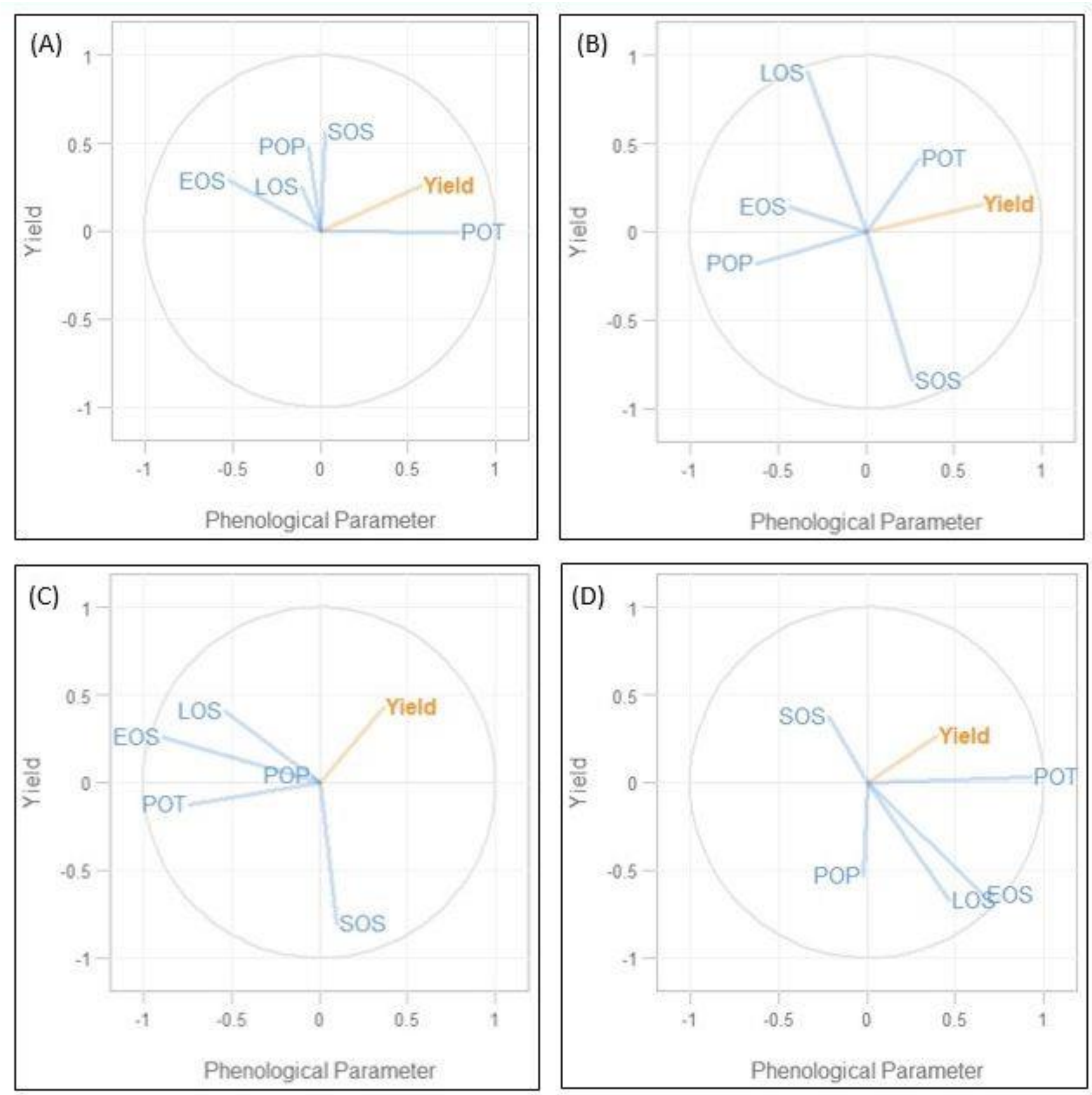

Figure 4-9: Circles of correlation the phenological parameters and weighted parameter yield in (a) FS: Free State, (b) KZN: KwaZulu-Natal, (c) MP: Mpumalanga, and (d) NW: North West

4.2.5. Impact of varying phenological parameters on maize yield

In this study multivariate analysis model was used to assess the relationships among maize yield, phenological parameters and climatic parameters. The multivariate analysis results are summarized in Table 4. As shown in Table 4, changes in phenological parameters can be associated to variations in the maize yield for the major maize producing areas ranging from 70% in Mpumalanga, 72% in KwaZulu-Natal, 76% in North West and 79% in Free State.

According to Table 4 from 2000 to 2015, there was an estimated reduction in the maize yield in the North West Province of about 0.01 tons per hectare (t/ha) when the climatic parameters and phenological parameters are held constant at their averages; that is when PET is 5.3 mm/day, PRE is 57 mm/month, TMN is 16 °C, TMX is 31 °C, SOS is on day 339, EOS is on day 117, LOS is 149 days, POP is on day 35 and POT is on day 225. However minimal increase of about 1% in the mean value of PET, PRE, and TMN led to an increase of about 0.47, 0.02, 0.30 t/ha in maize yield respectively while, increase of about 1% in the mean value of TMX led to reduction of about 0.05 t/ha in maize yield. On the other hand, at about 1% increase in the mean values of SOS, LOS, POP and POT there is decrease of about 1.44, 3.49, 1.39 0.89 t/ha of maize yield respectively; however, EOS increased maize yield by about 3.55 t/ha . In Mpumalanga Province, maize yield decreased by 0.003t/ha when the phenological parameters are at average values. Increase of about 1% above the average value in PRE (108 mm/month), TMX (25°C), SOS (day 309), and LOS (day 179) lead to a decrease of 0.39 t/ha, 0.35 t/ha, 1.56 t/ha, and 1.74t/ha in maize yield respectively. However, 1% increase in the average values of PET, TMN, EOS, POP, and POT increased maize yield by 0.46t/ha, 0.85t/ha, 0.28t/ha, 0.05t/ha and 0.01t/ha respectively. In KwaZulu-Natal Province, no change in maize yield per hectare was observed when average values of PET, PRE, TMN, TMX, SOS, EOS, LOS, POP and POT are held constant at 3.9 mm/day, 103 mm/month, 15 °C, 27°C, day 295, day 126, 194 days, day 20 and day 203 respectively. With a 1% increase in the mean values of PET, PRE, SOS, LOS and POT there is an increase of about 0.36 t/ha, 2.92 t/ha, 1.57 t/ha, 1.19 t/ha and 0.82 t/ha in maize yield respectively. However, maize yield reduced by about 0.26, 1.0, 1.24, 0.71 t/ha with 1% increase of the mean values of TMN, TMX, EOS and POP respectively. While in Free State, an increase of about 0.001 t/ha in the maize yield is estimated when the mean values of PET (5.2 mm/day), PRE (60 mm/month), TMN (13 °C), TMX (28 °C), SOS (day 329), EOS (day 112), LOS (148 days), POP (day 32) and POT (day 191) are held constant. Additionally, 1% increase in the average values of PRE, TMX, SOS, LOS, POP and POT lead to an increase of about 0.35 t/ha, 0.75 t/ha, 0.39 t/ha, 0.56 t/ha, 0.26 t/ha and 0.71 t/ha in maize yield respectively. While maize yield decreases by about 0.08 t/ha, 0.68 t/ha and 0.50 t/ha with 1% increase in the average values of PET, TMN and EOS.

Table 4-4: Coefficients of the model. Start of Season (SOS), End of Season (EOS), Length of Season (LOS), Position of Peak Value (POP) and Position of Trough Value (POT) (2000-2015); KwaZulu-Natal (KZN)

Province	**Crop**	**Constant**	**PET**	**PRE**	**TMN**	**TMX**	**SOS**	**EOS**	**LOS**	**POP**	**POT**	**R^2**
North West	Maize	-0.01	0.47	0.02	0.30	-0.05	-1.44	3.55	-3.49	-1.39	-0.89	0.76
Mpumalanga	Maize	-0.003	0.46	-0.39	0.85	-0.35	-1.56	0.28	-1.74	0.05	0.01	0.70

KZN	Maize	0.00	0.36	2.92	-0.26	-1.00	1.57	-1.24	1.19	-0.71	0.82	0.72
Free State	Maize	0.001	-0.08	0.35	-0.68	0.75	0.39	-0.50	0.56	0.26	0.71	0.79

The result of the multivariate analysis further indicates (figure 10), the relative importance of each phenological parameters. Positive values depict positive predictors while negative values show negative predictors. The EOS is the most influencing phenological parameter in both Free State and KwaZulu-Natal, however it is a negative influence. The SOS is the most influencing parameter in Mpumalanga and North West, though, it’s has a negative influence in Mpumalanga and positive influence in North West. The major positive phenological parameters linked to changes in maize yield are POT in Free State, SOS in both KwaZulu-Natal and North West, and POP in Mpumalanga.

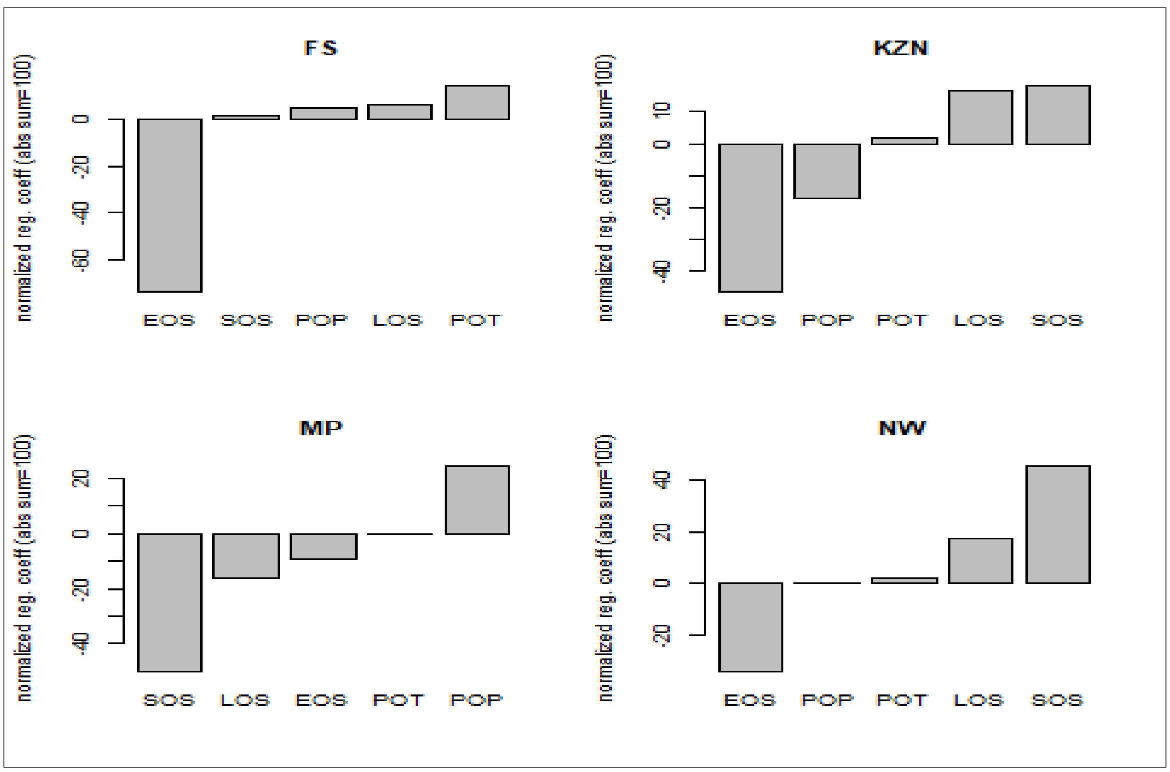

Figure 4-10: Normalised regression coefficient of maize yield predictors across the major maize producing Provinces of South Africa

4.2.6. Drivers of phenological changes and maize yield

The results of the PLS-PM model hinged on the hypothesis that changes in maize yield as a link to the changes in phenological parameters driven majorly by climatic factors among other factors. As shown in table 4, the result from the multivariate analysis indicate that TMN is the most significant driver of changes in the phenological parameters mostly influencing the POT in both

North West and Free State. In KZN, PET and TMX majorly drive the changes in phenology influencing EOS and SOS respectively while in Mpumalanga, PRE is detected as the major driver of phenological changes mostly influencing LOS. The reliability of the measurement of the relationship among the variables is given Cronbach's alpha coefficient shown in table 5 [41]. An estimated alpha of 0.841 for climate, 0.674 for phenology and 0.796 for yield indicating how well the indicators measure their corresponding latent construct.

Table 4-5: Unidimensionality metrics for the latent variables

	Mode	**MVs**	**C.alpha**	**DG.rho**	**eig.1st**	**eig.2nd**
Climate	A	4	0.841	0.907	2.928	1.058
Phenology	A	5	0.674	0.798	2.469	1.677
Yield	A	2	0.796	0.908	1.661	0.339

Similarly, variance of the sum of variables in the indicators is given as 0.907, 0.798 and 0.908 for climate, phenology and yield respectively by the Dillon Goldstein's rho [41]. The result of the PLS-PM further indicates that only the yield is unidimensional having first eigenvalue greater than 1 and second eigenvalue less than one. This result is further illustrated in figure 11 showing the loadings of the block with all indicators in blue arrows without any in red. Furthermore, as indicated by the coefficients of determination, R^2, shown in table 6; climate the independent latent variable is able to explain about 94% of variation in phenology and 99% of variation in yield.

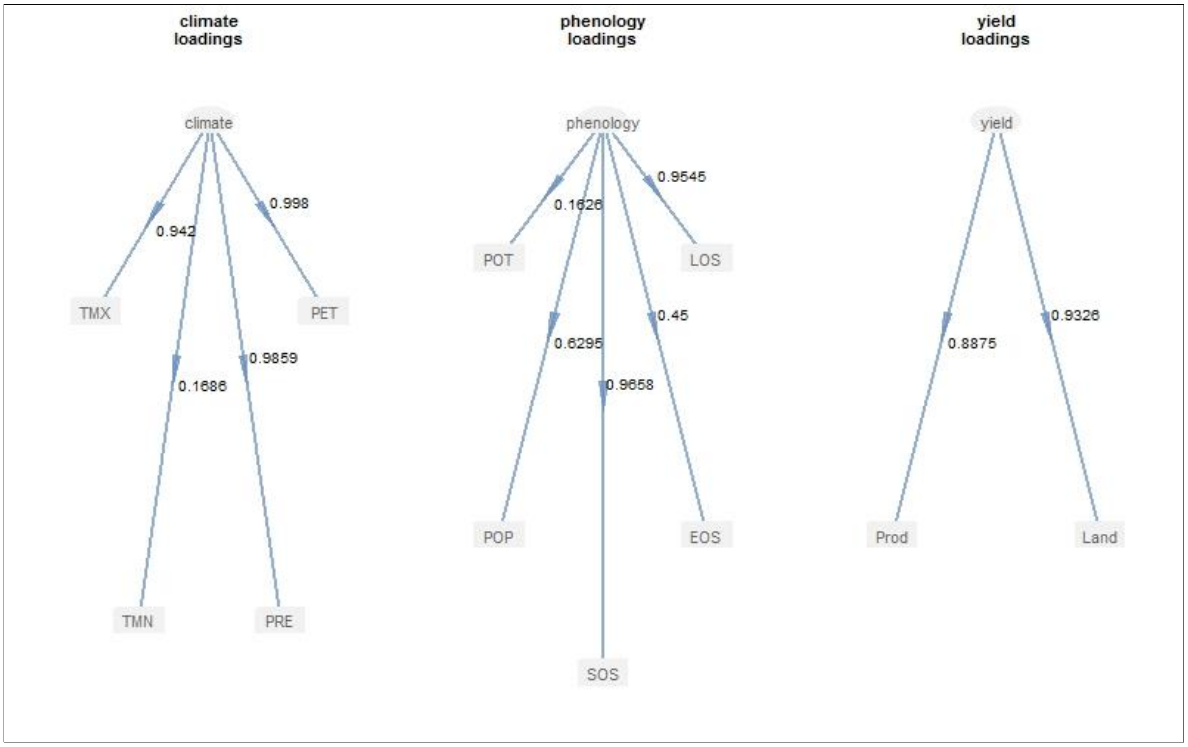

Figure 4-11: Loadings of blocks (latent variables) and the indicators

Table 4-6: Coefficients of determination R^2 of the endogenous latent variables

	Type	R^2	Block Communality	Mean Redundancy	AVE
Climate	Exogenous	0.000	0.721	0.000	0.521
Phenology	Endogenous	0.941	0.494	0.465	0.494
Yield	Endogenous	0.999	0.729	0.628	0.629

The Mean Redundancy represents the percentage of the variance in the endogenous blocks (phenology and yield) that is predicted from the independent LV (climate) the exogenous variable. As shown in table 6, it implies that climate is able to predict about 46% of the variability of phenology indicators and about 63% of the variability of yield indicator. The prediction power of the model assessed by the Goodness of fit indicate that the model has a prediction power of 75%.

4.3. Discussion

Previous studies [43-45] have shown that changes in crop yields could be linked to changes in the climatic conditions during the growing season. Sensitivity of the crop to wet and dry conditions and non-climatic factors like management practices, fertilizers, new varieties are have also been reported to affect crop yield.

Satellite-derived phenological parameters are frequently used to study the response of ecosystems to climate change. In this study, phenological parameters were derived from NDVI computed values. Trends and significant trends of the parameters were computed from the NDVI values. It was the hypothesised that changes in maize yield as a link to the changes in phenological parameters driven majorly by climatic factors among other factors. The results suggest that all the major maize producing Provinces considered in the present study exhibit negative NDVI trends (“browning”). However, the spatial analysis plot of the NDVI at pixel level across the municipalities of the study area reveals that there are positive but statistically insignificant trends in the NDVI time series. On the other hand, the detected negative trends are observed to be statistically significant at 5% significant level. The observed NDVI temporal variations can be attributed to factors such as high rainfall variability [46], cooling spring temperature as well as lead to increasing water vapour pressure deficit [47]. Cooling spring temperature could be detrimental to maize yield as it causes various types of physiological damage (chilling injury) on the crop [48]. On the other hand, increasing water vapour deficit may dry up the soil thereby reducing the soil moisture content and eventually maize yield [49].

One of the numerous effects resulting from inter-annual variability is breakpoints in NDVI time series. Inter-annual variability causes reduction in NDVI values (change in annual mean), prolonged growing season (as a result of longer warmer temperatures), and short-term patterns of the NDVI time series [41]. This is supported by the findings of this study. For instance, the LOS for all the years in which breakpoints were detected in the analysis indicated an increase in LOS (e.g. LOS in Mpumalanga increased from 142 days in 2003 to 186 days in 2004; in Free State it increased from 154 days in 2008 to 167 days in 2009; in North West it increased from 106 days in 2007 to 147 days and in KwaZulu-Natal it increased from 188 days in 2011 to 223 days in 2012). Furthermore, the results from this study revealed that for the whole study period, Free State, Mpumalanga and North West Provinces exhibited a late start of season as well as short growing season (see for instance results in Figure 4). This might be the cause of the non-significant increase in maize yield for these Provinces. Additionally, the variation in the phenological parameters for all the Provinces is proxy for detecting climate change signals. The earlier arrival of planting season can be traced to the recent warming trends in the global climate [46]. This disruption can have numerous impacts on the ecosystem and human society.

The trends in the phenological parameters is a pointer to the ongoing phenological changes which could be attributed to climate change. As reported by Reference [50], SOS variability is an important characteristic affecting crop production in semiarid areas. The results correspond with the findings of Reference [51]. The declining trend in SOS might further lead to low maize production. Generally, climate change [46], land degradation and other human activities such as over-grazing and bush burning [52] are major factors causing changes in NDVI and phenology parameters.

Previous studies have shown that increasing temperature during maize vegetative period leads to a decrease in the length of stage in growth [32]. In general, increased temperature led to lengthened growing seasons (LOS) for maize yield in KZN and MP. The year to year variations in trends observed in phenological parameters can be attributed to the fluctuations in the annual climatic factors. These fluctuations can be attributed to the various severe weather events such as droughts that have occurred in South Africa during the period of study. For instance, the breakpoints noticed in the time series coincides with drought years of 2002/2003, and 2012/2013 and hence could give an explanation for the declined trend in the maize yield during these periods. This inherent influence of climate variables causing changes in phenology have various consequences for plant physiological including maize [32]. The variation in the climatic variables influence on phenology and indirectly maize yield across the Provinces (76%, 70%, 72% and 79% in North West, Mpumalanga, KZN and Free State, respectively) might be due to the varying intensity in the use of irrigation, fertilizers and other farm managements. In addition, the prediction power of the model 75% as indicated from the GoF is acceptable and considered good [42].

Phenological parameters are considered as one of the most essential information that small-scale farmers require in their preparations for planting [49]. As deduced from the results of this study, farmers are advised to consider the crucial phenological parameters before cultivating maize. That is, it is important for farmers in Free State and KwaZulu-Natal Provinces to consider the time of end of measurable photosynthesis in the canopy (EOS) before cultivating maize in the area while those in Mpumalanga and North West should consider the beginning of measurable photosynthesis in the vegetation (SOS). Therefore, as one of the ultimate goals of agricultural production is to achieve maximum crop yield at minimum cost. Early detection and management of problems that are associated with crop yield indicators can assist in improving yield and subsequently increasing profit [52]. Stability in the maize production acreage in Free State Province could help reduce the variation in the maize production for the Province and ultimately help improve the output. With Mpumalanga Province having the second largest yield per hectare, an increase in the acreage for the area will greatly improve the maize production for the area. Furthermore, despite the fact that the acreage for maize production in the North West Province was usually more than that of Mpumalanga Province, maize produced in Mpumalanga was greater than that of North West Province in 2006, 2007, 2008, 2012, 2014 and 2015. This implies that Mpumalanga has the potential of increasing the maize production for South Africa if necessary facilities and infrastructures are provided.

4.4. Conclusions

The spatial-temporal phenological characteristics of the vegetation mimic the inherent vegetation responses to changes in environmental and climatic factors. Therefore, analysis of the phenological parameters for different types of vegetation in large areas helps to evaluate the impacts of climate change e.g., vulnerable ecosystems. At present, the phenology metrics that are derived from the time series of MODIS Normalized Difference Vegetation Index (NDVI) are recognized to provide an alternative methodology of crop condition monitoring compared to the expensive and time-consuming manual system. These phenological parameters have important applications such as in irrigation management, nutrient management, health management, yield prediction and crop type mapping vital for ensuring the security of the food crop production. Additionally, interest in crop phenology has increased recently because of the effect its variation has on surface roughness and albedo, which eventually affects latent and sensible heat flux and fluctuation of water from the surface to the atmosphere.

Every season, farmers are always faced with the risk of losing their crops and eventually losing their income. In order to achieve maximal output, it is imperative to consider the favourable climatic conditions for planting crop, since for instance maize farming depends on climatic factors (like rainfall, radiation and temperature). The determination of suitable climatic conditions (particularly knowing the optimum time to plant) can be done using the phenological parameters. Hence, this study investigated the relationship between climatic variables, phenological parameters and maize production in four Provinces of South Africa. As a means of properly managing the inevitable climate change impacts for a sustainable South Africa (an objective of National Climate Change Response Policy (NCCRP)), this study provides the phenological parameters for maize producing areas of South Africa that can be used for proper management of crop production. Results from this study illustrate inherent spatial-temporal characteristics of the MODIS NDVI derived phenology metrics. In addition, analysis of the phenological metrics to assess the spatial and temporal crop yield variability across maize growing Provinces in South Africa show subtle associations largely due to insufficient intra-seasonal maize growth dynamics.

In addition, with established evidence of climate change, reports have shown that frequency and intensity of extreme events with potentials to affect crop production might be on the increase, having more devastating impact on low coping capacity countries. Therefore, the need to mitigate against or adapt to climate change, through adequate cropping systems, improved crop cultivar among others is become imperative for farmers [53]. These results can be used as a benchmark by farmers to access information about climate change and variability and the associated impacts on maize production. This knowledge will help farmers to seek adaptation measures to ensure that seedlings are not lost for good crop yield. In addition, study such as this can be used as a tool to assess the vulnerability of agriculture/farms (particularly maize farms) to climate change which can help smallholder farmers to provide evidence to have access to insurance benefits and loans [54] Furthermore, reliable high-quality long-term remote sensing datasets, such as the MODIS NDVI dataset, are a crucial input for providing converging evidence on vegetation changes. While much is to be learned regarding the human dimension of adaptation, such evidence is highly needed to inform potential adaptation strategies for smallholder farmers in South Africa. A major limitation of this study is the lack of availability of maize data at higher scale i.e., at intra-season and at the farm level. If such data is available it could help to further establish the relationship between the phenological parameters and maize production at seasonal and farm level. Also, the inclusion of non-climatic data such as management practices (irrigation, fertilizers application, new improved seedlings, multi-cropping) could be vital in improving the PLS-PM model.

Acknowledgments: I will like to acknowledge the University of Pretoria and DST for providing student bursary and publication fee through the EU FP7 AnimalChange project under the grant agreements no. 266018.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Maignan, F.; Bieon, F.M.; Baccour, C.; Demarty, J.; Poirson, A. Interannual vegetation phenology estimates from global AVHRR measurements: comparison with in situ data and application. *Remote Sens. Environ.* **2008,** 112, 496-505.

2. Jolly, W.M.; Running, S.W. Effects of precipitation and soil water potential on drought deciduous phenology in the Kalahari. *Glob. Chang. Biol*. **2004,** 10, 303–308.

3. Cleland, E.E.; Chuine, I.; Menzel, A.; Mooney, H.A.; Schwartz, M.D. Shifting plant phenology in response to global change. *Trends Ecol. Evol*. **2007,** 22, 357–365.

4. Hong, X.; Tracy, E.T.; and Xi Y. Evaluating remotely sensed phenological metrics in a dynamic ecosystem model. *Remote Sens*. **2014**, 6, 4660-4686; doi:10.3390/rs6064660

5. IPCC Climate Change 2007: The Physical Science Basis. In *Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK; New York, NY, USA, **2007**.

6. Xiaoming, K.; Yanbin, H.; Xiaoyong, C.; Huai, C.; Sanxiang, H.; Yangong, D.; Wei, L.; Paul, K.; Xiangming, X.; and Lijuan, C. Variability and Changes in Climate, Phenology, and Gross Primary Production of an Alpine Wetland Ecosystem, *Remote Sens*. **2016**, 8, 391; doi:10.3390/rs8050391

7. Zhou, L.; Tucker, C.J.; Kaufmann, R.K.; Slayback, D.; Shabanov, N.V.; Myneni, R.B. Variation in northern vegetation activity inferred from satellite data of vegetation index during 1981 to 1999. *J. Geophys. Res*. **2001**, 106, 20069–20083.

8. Zhu, W.; Tian, H.; Xu, X.; Pan, Y.; Chen, G.; Lin, W. Extension of the growing season due to delayed autumn over mid and high latitudes in north America during 1982–2006. *Glob. Ecol. Biogeogr*. **2012**, 21, 260–271.

9. Tesfaye, K.; Aggarwal, P.K.; Mequanint, F.; Shirsath, P.B.; Stirling, C.M.; Khatri-Chhetri, A.; Rahut, D.B. Climate Variability and Change in Bihar, India: Challenges and Opportunities for Sustainable Crop Production. *Sustainability* **2017**, 9, 1998.

10. Gourav, M.; Allan, B.; and Annette, M. Effects of Different Methods on the Comparison between Land Surface and Ground Phenology—A methodological case study from south-western Germany. *Remote Sens*. **2016**, 8, 753; doi:10.3390/rs8090753.

11. Badeck, F.W.; Bondeau, A.; Böttcher, K.; Doktor, D.; Lucht, W.; Schaber, J.; Sitch, S. Responses of spring phenology to climate change. *New Phytol*. **2004**, 162, 295–309.

12. Galina, C.; David, S.; Braswell, B.H.; Xiao, X. Spatial analysis of growing season length control over net ecosystem exchange. *Glob. Chang. Biol*. **2005**, 11, 1777–1787.

13. Kimball, J.; Zhao, M.; McDonald, K.; Running, S. Satellite remote sensing of terrestrial net primary production for the pan-arctic basin and Alaska. Mitig. Adapt. Strateg. *Glob. Chang*. **2006**, 11, 783–804.

14. Duchemin, B.; Hadria, R.; Rodriguez, J.C.; Lahrouni, A.; Khabba, S.; Boulet, G.; Mougenot, B.; Maisongrande, P.; Watts, C. Spatialisation of a crop model using phenology derived from remote sensing data. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '03), Toulouse, France, 21–25 July **2003**; pp. 2200–2202.

15. Lobell, D.B.; Asner, G.P.; Ortiz-Monasterio, J.I.; Benning, T.L. Remote sensing of regional crop production in the Vaqui valley, Mexico: Estimates and uncertainties. *Agric. Ecosyst. Environ*. **2003**, 94, 205–220.

16. Wang, L.; Ning, Z.; Wang, H.; Ge, Q. Impact of Climate Variability on Flowering Phenology and Its Implications for the Schedule of Blossom Festivals. *Sustainability* **2017**, *9*, 1127.

17. Lee, S.-D. Global Warming Leading to Phenological Responses in the Process of Urbanization, South Korea. *Sustainability* **2017**, *9*, 2203.

18. Tateishi, R.; Ebata, M. Analysis of phenological change patterns using 1982–2000 advanced very high resolution radiometer (avhrr) data. *Int. J. Remote Sens*. **2004**, 25, 2287–2300.

19. Xu, D.; Fu, M. Detection and Modeling of Vegetation Phenology Spatiotemporal Characteristics in the Middle Part of the Huai River Region in China. *Sustainability* **2015**, *7*, 2841-2857.

20. Forkel, M.; Migliavacca, M.; Thonicke, K.; Reichstein, M.; Schaphoff, S.; Weber, U.; Carvalhais, N. Codominant water control on global interannual variability and trends in land surface phenology and greenness. *Glob. Chang. Biol*. **2015**, 3414–3435.

21. Zhang, X.; Goldberg, M.D. Monitoring fall foliage coloration dynamics using time-series satellite data. *Remote Sens. Environ*. **2011**, 115, 382–391.

22. Ma, X.; Huete, A.; Yu, Q.; Coupe, N.R.; Davies, K.; Broich, M.; Ratana, P.; Beringer, J.; Hutley, L.B.; Cleverly, J.; et al. Spatial patterns and temporal dynamics in savanna vegetation phenology across the north Australian tropical transect. *Remote Sens. Environ*. **2013**, 139, 97–115.

23. Guyon, D.; Guillot, M.; Vitasse, Y.; Cardot, H.; Hagolle, O.; Delzon, S.; Wigneron, J.P. Monitoring elevation variations in leaf phenology of deciduous broadleaf forests from spot/vegetation time-series. *Remote Sens. Environ*. **2011**, 115, 615–627.

24. Atkinson, P.M.; Jeganathan, C.; Dash, J.; Atzberger, C. Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. *Remote Sens. Environ*. **2012**, 123, 400–417.

25. Gitelson, A.A. Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. *J. Plant Physiol*. **2004**, 161, 165–173.

26. Zhao, B.; Yan, Y.; Guo, H.; He, M.; Gu, Y.; Li, B. Monitoring rapid vegetation succession in estuarine wetland using time series MODIS-based indicators: An application in the Yangtze river delta area. *Ecol. Indic*. **2009**, 9, 346–356.

27. Gamon, J.A.; Field, C.B.; Goulden, M.L.; Griffin, K.L.; Hartley, E.; Joel, G.; Peñuelas, J.; Valentini, R. Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. *Ecol. Appl.* **1995**, *5*, 28–41.

28. Turner, D.P.; Cohen, W.B.; Kennedy, R.E.; Fassnacht, K.S.; Briggs, J.M. Relationships between leaf area index and Landsat TM spectral vegetation indices across three temperate zone sites. *Remote Sens. Environ.* **1999**, *70*, 52–68.

29. Fensholt, R.; Sandholt, I.; Rasmussen, M.S. Evaluation of Modis LAI, FAPAR and the relation between FAPAR and NDVI in a semi-arid environment using *in situ* measurements. *Remote Sens. Environ.* **2004**, *91*, 490–507.

30. Toshihiro, S.; Brian, D.W.; Anatoly, A.G.; Shashi, B.V.; Andrew, E.S.; Timothy, J.A. A Two-Step Filtering approach for detecting maize and soybean phenology with time-series MODIS data. *Remote Sens. Environ.* **2010**, 114, 2146–2159.

31. Viña, A.; Gitelson, A.A.; Rundquist, D.C.; Keydan, G.P.; Leavitt, B.; and Schepers, J. "Monitoring Maize (Zea mays L.) Phenology with Remote Sensing". *Papers Nat. Res.* **2004**, 264. Available online: http://digitalcommons.unl.edu/natrespapers/264 (accessed on 18 May 2018).

32. Liu, Y.; Xie, R.; Hou, P.; Li, S.; Zhang, H.; Ming, B.; Long, H.; Liang, S. Phenological responses of maize to changes in environment when grown at different latitudes in China. *Field Crops Res.* **2013**, *144*, 192–199.

33. Botai, C. M; Botai, J.O; Dlamini, L.C; Zwane, N.S; Phaduli, E. Characteristics of Droughts in South Africa: A Case Study of Free State and North West Provinces. *Water* **2016**, 8, 439, doi:10.3390/w8100439.

34. Botai, C. M; Botai, J.O; de Wit, J.C; Ncongwane, K.P; Adeola, A.M. Drought Characteristics over the Western Cape Province, South Africa. *Water* **2017**, 9, 876, doi:10.3390/w9110876.

35. Adisa, O.M.; Botai, C.M.; Botai, J.O.; Hassen, A.; Darkey, D.; Tesfamariam, E.; Adisa, A.F.; Adeola, A.M.; Ncongwane, K.P. Analysis of agro-climatic parameters and their influence on maize production in South Africa. *Theor. Appl. Climatol.* **2017**, doi.org/10.1007/s00704-017-2327-y.

36. Tadross, M.A.; Hewitson, B.C.; and Usman, M.T. The interannual variability of the onset of the maize growing season over South Africa and Zimbabwe. *J. Clim.* **2005**, 18 3356–3372.

37. Harris, I.; Jones, P.D.; Osborn, T.J; Lister, D.H. Updated highresolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *Int. J. Climatol.* **2014**, 34, 623–642. doi:10.1002/joc.3711.

38. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. Crop evapotranspiration-Guidelines for computing crop water requirements. Irrigation and drainage. FAO, **1998**. 56, 300, 6541.

39. Lorenzo, B.; Luigi, R. MODIStsp: A Tool for Automatic Preprocessing of MODIS Time Series. *Comput. Geosci.* **2017**. 97, 40-48.

40. Forkel, M.; Wutzler, T. Greenbrown - land surface phenology and trend analysis. A package for the R software. Version 2.2, 15 April **2015**. Available online: http://greenbrown.r-forge.r-project.org/. (accessed on 18 May 2018).

41. Forkel, M.; Carvalhais, N.; Jan Verbesselt; Mahecha, M.D.; Neigh, C.S.R.; Reichstein, M. Trend change detection in NDVI time series: Effects of inter-annual variability and methodology. *Remote Sens*. **2013**, 5, 2113-2144.

42. Sanchez, G.; PLS Path Modeling with R. Trowchez Editions. *Berkeley*. **2013**. Available online: http://www.gastonsanchez.com/PLS Path Modeling with R.pdf (accessed on 18 May 2018).

43. USDA/NASS. National Crop Progress—Terms and Definitions. Available online: http://www.nass.usda.gov/Publications/National_Crop_Progress/Terms_and_Definitions/index.asp (accessed on 24 May 2018).

44. Potopová, V.; Boronean¸t, C.; Boincean, B.; Soukup, J. Impact of agricultural drought on main crop yields in the Republic of Moldova. *Int. J. Climatol.* **2016**, 36, 2063–2082.

45. Lobell, D.B.; Asner, G.P. Climate and management contributions to recent trends in US agricultural yields. *Science* **2003**, 299, 1–17.

46. Richardson, A.D.; Keenan, T.F.; Migliavacca, M.; Ryu, Y.; Sonnentag, O.; Toomey, M. Climate change, phenology, and phenological control of vegetation feedbacks to the climate system. *Agric. For. Meteorol*. **2013**, 169, 156–173.

47. Goetz, S.J.; Bunn, A.G.; Fiske, G.J.; Houghton, R.A. Satellite-observed photosynthetic trends across boreal north america associated with climate and fire disturbance. *Proc. Natl. Acad. Sci. USA* **2005**, 102, 13521–13525.

48. Wu, H.; Hubbard, K.G.; Wilhite, D.A. An agricultural drought risk-assessment model for corn and soybeans. *Int. J. Climatol.* **2004**, 24, 723–741.

49. Van Wart, J.; Kersebaum, K.C.; Peng, S.; Milner, M.; Cassman, K.G. Estimating crop yield potential at regional to national scales. *Field Crops Res*. **2013**, 143, 34-43.

50. Vrieling, A.; de Beurs, K.M.; Brown, M.E. Variability of African farming systems from phenological analysis of NDVI time series. *Clim. Chang.* **2011**, 109, 455–477.

51. Jayawardhana, W.G.N.N.; and Chathurange, V.M.I. *Extraction of Agricultural Phenological Parameters of Sri Lanka Using MODIS, NDVI Time Series Data;* Published by Elsevier Ltd.: New York, NY, USA, **2016**, doi: 10.1016/j.profoo.2016.02.027.

52. Zika, M.; Erb, K.-H. The global loss of net primary production resulting from human-induced soil degradation in drylands. *Ecol. Econ*. **2009**, 69, 310–318.

53. Waha, K.; Müller, C.; Bondeau, A.; Dietrich, J.P.; Kurukulasuriya, P.; Heinke, J.; Lotze-Campen, H. Adaptation to climate change through the choice of cropping system and sowing date in Sub-saharan Africa. *Glob. Environ. Chang.* **2013**, *23*, 130–143.

54. Dalhaus, T.; Musshoff, O;, Finger, R. Phenology information contributes to reduce temporal basis risk in agricultural weather index insurance. *Sci. Rep.* **2018**, 8, 46, doi:10.1038/s41598-017-18656-5.

Chapter 5

INFLUENCE OF DROUGHT ON MAIZE PRODUCTION

Analysis of drought conditions over major maize producing provinces of South Africa

Omolola M. Adisa[1,*], Joel O. Botai[1,2,3], Abiodun M. Adeola[2,4], Christina M. Botai[2], Abubeker Hassen[5], Daniel Darkey[1], Eyob Tesfamariam[6], Abidemi T. Adisa[7], and Alex F. Adisa[8]

[1]Department of Geography, Geoinformatics & Meteorology, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; lolaadisa@yahoo.com OMA; daniel.darkey@up.ac.za DD

[2]South African Weather Service, Private Bag X097, Pretoria 0001; joel.botai@weathersa.co.za JOB; abiodun.adeola@weathersa.co.za AMA; christina.botai@weathersa.co.za CMB

[3]School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal,

Westville Campus, Private Bag X54001, Durban 4000, South Africa

[4]School of Health Systems and Public Health, Faculty of Health Sciences, University of Pretoria

[5]Department of Animal and Wildlife Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; abubeker.hassen@up.ac.za (AH)

[6]Department of Plant and Soil Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; eyob.tesfamariam@up.ac.za ET

[7]Department of Agricultural and Applied Economics, Texas Tech University, Lubbock Texas, USA; abidemi.adisa@ttu.edu ATA

[8]Department of Agricultural Engineering, Federal University of Agriculture, Abeokuta, Nigeria; alexadisa@yahoo.co.uk AFA

* Corresponding author. u13387562@tuks.co.za; Tel.: +27 84 849 1170

This article has been accepted for publication with Journal of Agricultural Meteorology, https://www.editorialmanager.com/agrmet/default.aspx

Abstract

In this study, two commonly used drought indices; the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI), were analyzed in order to understand the impacts of drought on maize yield over four main maize production provinces of South Africa. The drought was characterized using three Drought Monitoring Indicators (DMI) i.e., the Drought Duration (DD), Drought Severity (DS), and Consecutive Drought Months (CDM). The results indicate that maize yield is significantly affected by drought across the entire study area, although the impacts are localized. A comparison between the SPI and SPEI with maize yield suggests that the SPEI is more correlated and sensitive to maize yield than the SPI. The maize yield is particularly most sensitive to the 3-month SPEI. The 3-month accumulation period coincides with maize growing season ($r = 0.59$; $p < 0.05$). The analyzed results illustrate that drought affects maize yield by up to 35% across the study area. Additionally, results depict inherent spatial patterns of DMIs demonstrating that there are differentiated drought impacts across the maize production areas. The results suggest that management strategies that allow for optimal water use within the first 1- and 3-month periods would be most effective for sustainable maize production within the study area. This research study contributes towards a deeper understanding of the characteristics of drought and their impacts on maize crop production. Such knowledge is important in e.g., the formulation of drought monitoring and prediction strategies including drought early warning systems.

Keywords: Agriculture; Climate, Drought; Maize; Yield

5.0. Introduction

Drought is considered as a slow and creeping recurring natural phenomenon (Wilhite, 2000). The effects of drought are manifested in many economic as well as social sectors. In agricultural sector, drought is considered as one of the major cause that leads to crop yield failure, particularly in both rain-fed and irrigated agro-ecosystems (Grayson, 2013; Zhang and Zhang, 2016). Recently (2016 – 2018), South Africa has experienced prolonged drought (Botai et al., 2016; 2017) that has affected both agricultural production and water resources, with the impacts already propagated into socio-economic. Due to persistent and widespread severe drought impacts in the country, robust emphasis on understanding the impacts this natural hazard as on key economic sectors is warranted. Research studies on drought issues include understanding drought characteristics, (e.g.

the onset, duration, intensity, magnitude, spatial extent, etc.). Such information is essentially important for better preparedness and proper management of key socio-economic sectors such as water and agriculture, which promote water quality and food security at regional as well as national level (Kurniasih and Impron, 2017).

Drought indices such as the Palmer Drought Severity Index (PDSI) (Palmer, 1968), the Crop Moisture Index (CMI) (Palmer, 1968), the Soil Moisture Drought Index (SMDI) (Hollinger, et al., 1993), the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), the Effective Drought Index (EDI) (Byun and Wilhite, 1999), the Agricultural Reference Index for Drought (ARID) (Woli et al., 2013), and the Vegetation Health Index (VHI) (Dalezios et al., 2014) are widely used by various agencies and researchers as tools for drought assessment, monitoring, analysis and alert, with the aim being to derive effective early warning drought monitoring systems for detecting and responding to potential future drought risks. Most of these indices are selected based on various factors that include the nature of the hydro-climatology of the region, the type of drought considered, the purpose of the study and the available data (Morid et al., 2006).

The SPI is the most commonly used drought index and well recommended by the World Meteorological Organization (Potop et al., 2012; Chen et al., 2013), as it is flexible in monitoring all the three types of drought (e.g. meteorological, agricultural, and hydrological). This index is primarily based on precipitation, whereas, its counterpart, the SPEI requires both precipitation and potential evapotranspiration information (PET), which is often computed from the minimum and maximum temperatures. Both the SPI and SPEI drought indices have the capability to detect and depict drought on a multi-temporal scales. In particular, the SPI and SPEI at 1-, 3-, and 6-accumulation months are often used to assess meteorological to agricultural drought impacts, whereas the 12 months and above (up to 24) are ideal for the hydrological socio-economic impacts, respectively (Morid et al., 2006; Potop et al., 2014).

A number of research studies analyzing and monitoring drought cases based on the SPI and SPEI drought indices have being reported in the literature (e.g., Chen et al., 2016; Botai et al., 2016; Meroni et al., 2017; Botai et al., 2017). Other studies have demonstrated the application of SPI or SPEI or a combination of both and other drought indices as tools for measuring and monitoring drought and its impacts on agricultural production (Ceglar et al., 2012; Mansouri et al., 2013; Dutta et al., 2015; Chen et al., 2016; Zipper et al., 2016; Kurniasih and Impron, 2017). In South Africa, most of the research studies have focused on drought assessment and monitoring (e.g. Edossa et al., 2014; Rouault and Richard, 2003; Botai et al., 2016 and 2017) with no-direct link to a specific type of drought. The only study that related drought to agriculture was reported by Masupha and Moeletsi (2017), although the authors considered the SPEI-1, which often reflects short-term conditions of soil moisture and crop stress.

The recent droughts (e.g. 2016 – 2018) that have affected at least five South African provinces have renewed the need for more research on the drought impacts and the need for effective planning to assist in mitigating feasible inherent effects of drought. Maize production is the most important grain crop in South Africa, accounting to approximately 46.2% of the gross value of field crops (DAFF, 2017). Drought persistence has the potential to create significant and devastating maize production challenges, leading to economic and financial difficulties for agricultural producers. To alleviate farm revenue losses and support government policy-makers on drought issues, there's a need to qualitatively evaluate the impacts of drought on maize production. For this purpose, the aim of this study is to investigate the impacts and the characteristics of drought in major maize producing provinces of South Africa based on the SPI and SPEI 1-, 3-, 6- and 12-month timescales during the main crop growth stages of October to April. In particular, the specific objectives of the current study are defined as follows: 1) to characterize the drought conditions using monitoring indicators (i.e., the drought duration, severity and magnitude); and 2) to determine the most significant index and timescale for which marginal maize yield is sensitive to and 3) to describe the association of drought monitoring indicators to spatiotemporal contrast of maize production.

5.1. Materials and methods

5.1.1. Study area

The study area includes the north-eastern part of South Africa between longitude 22^{o}E to 33^{o}E and latitude -32^{o}S to -24^{o}S. It covers the KwaZulu-Natal (KZN), Free State (FS), Mpumalanga (MP) and North West (NW) provinces (see Fig. 1). The FS, MP and NW provinces fall within regions that receive less than 600 mm of rainfall per year. In 2017 season, these provinces accounted for about 87% of the total maize produced in South Africa. In particular, MP province accounted for 20%, while NW, FS, and KZN provinces accounted for 19%, 44% and 4% of total maize production respectively. The FS and NW provinces contributed about 78% of the total white maize produced in 2017 while the FS and MP produced about 67% of the total yellow maize harvested. Most crops including maize are grown between October and March period. The FS province is characterized by chilly winters (ranging from a cold 1°C to mild 17°C), plenty of sunshine (15°C to 32°C) and summer rains (500 mm-600 mm annually). Located in the north-eastern part of the country, is the Vaal irrigated area which nourishes the small assortment of farming towns. In NW province there is almost a year-round sunshine, with an average rainfall of 300 to 600 mm annually. The summer temperature ranges from 22°C to 34°C. The NW province is characterized by dry, sunny days and chilly nights during winter (2°C to 20°C) season.

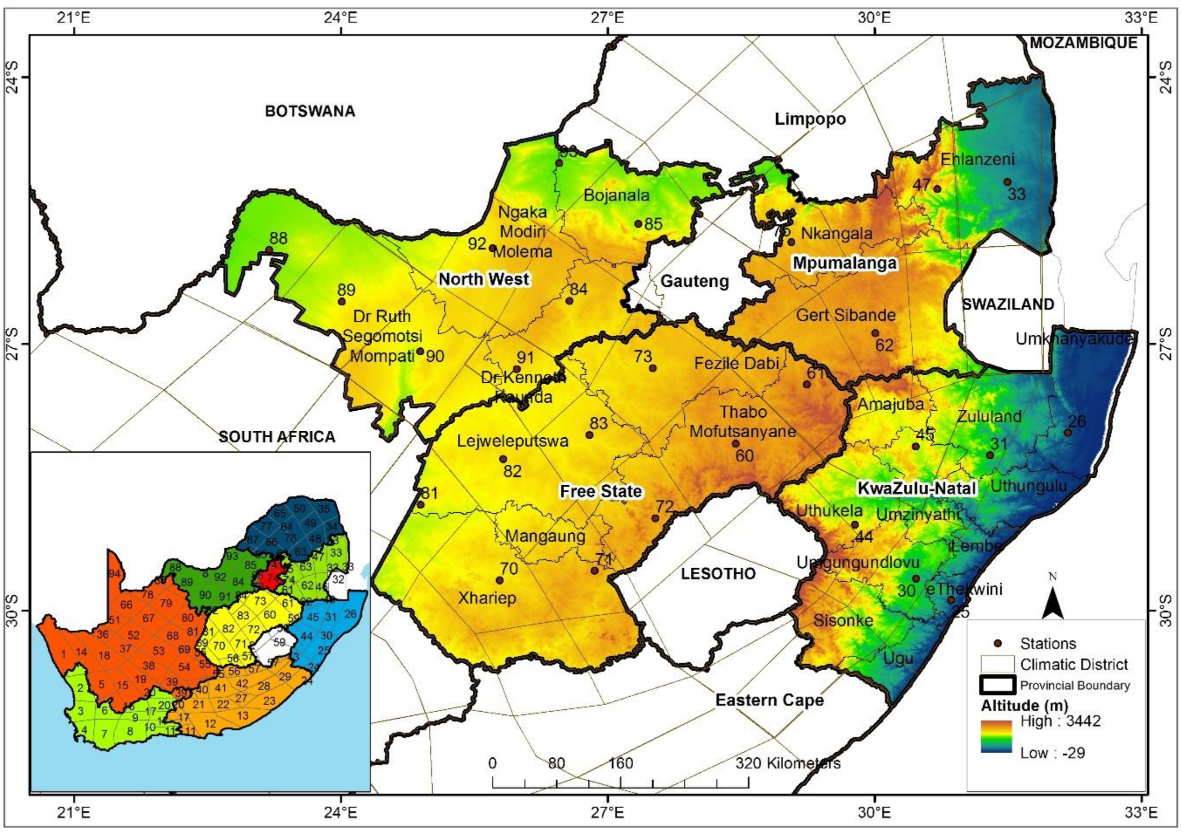

Figure 5-1:Study area showing elevation, South African Weather Service climatic districts and centroids of the climatic districts in the proximity of stations with provincial borders superimposed.

The temperature in KZN ranges between 23°C to 33°C in summer (December - February), and 16°C to 25°C during winter (June-August). The province is characterized by long, hot summers with average annual rainfall ranging between 500 mm and 900 mm, and mild winters. Furthermore, the western part of the MP province is much colder during winter and hotter during summer than the other parts of the province. The average annual temperature is about 19°C and rainfall is between 500 mm and 800 mm annually. The time series of total monthly precipitation, average monthly maximum (TMX), minimum (TMN) and mean (TMED) temperature, potential evapotranspiration (PET) and water deficit (BAL) over each province is given in Fig. 2.

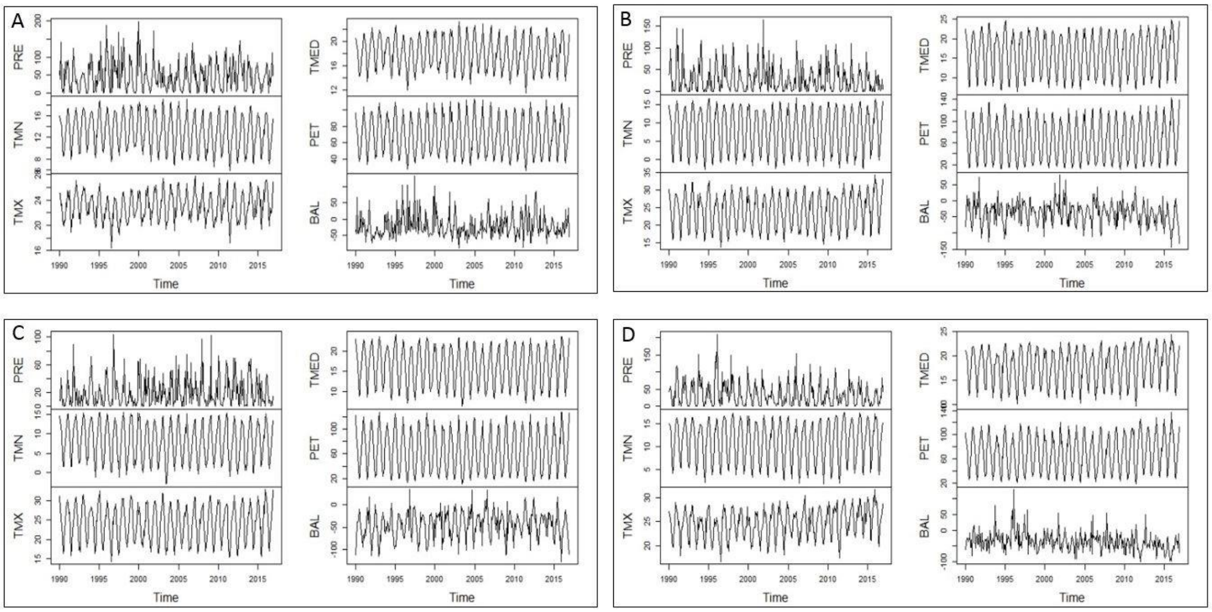

Figure 5-2: The time series of total monthly precipitation, average monthly maximum (TMX), minimum (TMN) and mean (TMED) temperature, potential evapotranspiration (PET) and water deficit (BAL) from 1990–2015 in A: Mpumalanga, B: Free State, C: North West and D: KwaZulu-Natal provinces

5.1.2. Materials

Pre-processed gridded historical observations of daily precipitation, minimum and maximum temperature from 27 ground stations (6 in KZN, 4 in MP, 8 in NW and 9 in FS) (see Fig. 1) spanning from 1990 to 2015, over the study area, were acquired from the South African Weather Service (SAWS). The maize production data sets in tons from 1990 to 2015 were obtained from the Abstract of Agricultural Statistics compiled by the Department of Agriculture, Forestry, and Fisheries of South Africa. The abstract document contains important information on *inter alia*, field crops, horticulture, livestock, vital indicators and the total land area in hectares (ha) used for maize production among others.

5.1.3. Methods

5.1.3.1. Analysis of drought by SPI and SPEI

In this contribution, we investigated the characteristics of drought over the major maize producing provinces of South Africa using the SPI and SPEI at 1-, 3-, 6-, and 12-month timescales. The advantages of using SPI and SPEI are premised on the principle of parsimony and their ability to quantify the magnitude, duration, and extent of droughts independently of the local climatic conditions and less data intensive. Both the SPI and SPEI at 1-, 3-, 6- and 12-month timescales were computed using the SPEI package in R software (Beguería and Vicente-Serrano, 2013; Vicente-Serrano *et al.,* 2015). The SPI is calculated by fitting a gamma distribution to a precipitation time series (McKee *et al.,* 1993). On the other hand, to compute the SPEI, the computation of "climatic water balance"; the difference between precipitation and reference evapotranspiration (PRE– PET_0), rather than precipitation (PRE) as the input in the case of SPI is required. Although, the Penman-Monteith (PM) method (Allen *et al.,* 1998) has been adopted by the International Commission for Irrigation (ICID), the Food and Agriculture Organization of the United Nations (FAO), and the American Society of Civil Engineers (ASCE) as the standard procedure for computing PET, the Thornthwaite (1948) equation was adopted for this research. The Thornthwaite equation requires only mean daily temperature and latitude of the site rather than the extensive data requirement of the PM equation (Solar radiation, relative humidity, wind speed and temperature) which are in most case not routinely measured at many conventional meteorological stations and long-term records of these variables are lacking. In this study, drought was characterized based on the classification summarized in Table 1. A drought event begins when the SPI or SPEI reaches a value of -1.0 or less and ends when SPI or SPEI becomes positive. It has been determined that SPI or SPEI is in normal, moderate, severe and extreme drought condition at 65%, 10%, 5% and 2% of the time respectively. In this study, it is considered that all the negative values were related to dry conditions. Hence, drought duration (DD), is defined as the longest period of consecutive months with the values <0. On the other hand, consecutive drought month (CDM) also referred to as drought magnitude is defined as the sum of the index values while drought severity (DS) is defined as the number of months with values <0 during the maize growing period.

Table 5-1: SPI and SPEI categories of drought

SPI/SPEI	Moisture category	Frequency (%)
≥2.0	Extreme Wet	2
1.50 to 1.99	Severe Wet	6
1.49 to 1.00	Moderate Wet	10
0.99 to -0.99	Normal	65
-1.00 to -1.49	Moderate Drought	10
-1.5 to - 1.99	Severe Drought	5
≤-2.00	Extreme Drought	2

5.1.3.2. Trend Analysis

Trend analysis was performed to determine if there exists significant variation in the datasets over the period of study. The analysis was performed by using the rank-based Mann–Kendall (MK) trend test. Before the MK test was applied, the effect of autocorrelation of data series was firstly removed by applying the trend-free pre-whitening procedure (Yue *et al.*, 2002). The magnitude of the trends was quantified using the Theil–Sen estimator. To compute the trends as well as the Theil–Sen estimator, the regional Kendall test (rkt) package in R software was used (Marchetto, 2017).

5.1.3.3. Statistical model fitting and spatial analysis

Correlation analysis was used to assess the relationship between the SPI, SPEI and maize yield at different timescales. Since maize is grown in the summer period of the year, only the SPI and SPEI values, calculated from October (maize sowing) until April (maize ripening) have been used in the analysis for each of the four provinces. The estimate yield per unit area was derived by dividing total cultivated area by total production in each province. The slope, the adjusted coefficient of determination (R^2), and the *p*-values were used to evaluate the relationship between the drought indices and maize yield. For each province, the best relationship was defined as the timing (i.e. the month of the growing season) and timescale (i.e. drought duration) combination with the highest adjusted R^2 (Vicente-Serrano *et al.*, 2012). Spatial distribution of SPI, SPEI, DD, DS, CDM, the coefficient of variation (CV), trend and p-values over each of the province were generated by interpolation from the point measuring stations using the inverse-distance-weighted (IDW) algorithm in ArcGIS desktop software (Rhee et al., 2008; Ali *et al.*, 2011; Vasiliades and Loukas, 2013; Chen *et al.*, 2017).

5.2. Results

5.2.1. Contrasts of maize yield across the study area

Over the 26 years under investigation, a total of 216,767 million tons of maize was produced across the study area. The highest maize production was recorded in the FS province with about 90,019 million tons (41.5%), followed by the NW with 60,838 million tons (28.1%), MP produced 55,823 million tons (25.8%) and a total of 10,087 million tons (4.6%) was produced in KZN. The analysis revealed that all four provinces experienced a major decline in the production of maize during 1991 and it's significant at p-value = 0.003 (Fig. 3). On the other hand, higher maize production was recorded between 2012 and 2013 in KZN, MP (2012) and FS (2013). The NW province exhibited high maize production in 1993. As shown in Table 2, the highest, lowest and mean maize production in FS is given as 6,247 million, 0,850 million and 3,462 million tons respectively. In KZN the highest maize produced was about 0,599 million tons, lowest of about 0,237 million tons with a mean of 0,388 million tons while in MP the highest production was 3,005 million tons with lowest of about 1,092 million tons and mean 2,147 million tons. Similarly, the highest production in NW was 3,635 million tons, lowest of 0,404 million tons and mean of 2,340 million tons over the period of study.

Table 5-2: Statistics of maize production million (tons) and coefficient of variation of maize yield across the four provinces

Statistics/Province	Free State	KwaZulu-Natal	Mpumalanga	North West
Minimum	850	237	1092	404
1st Quartile	2711	299	1766	1748
Median	3326	372	2182	2571
Mean	3462	388	2147	2340
3rd Quartile	4300	487	2636	2867
Maximum	6247	599	3005	3635
CV (Yield)	0.305	0.265	0.316	0.348

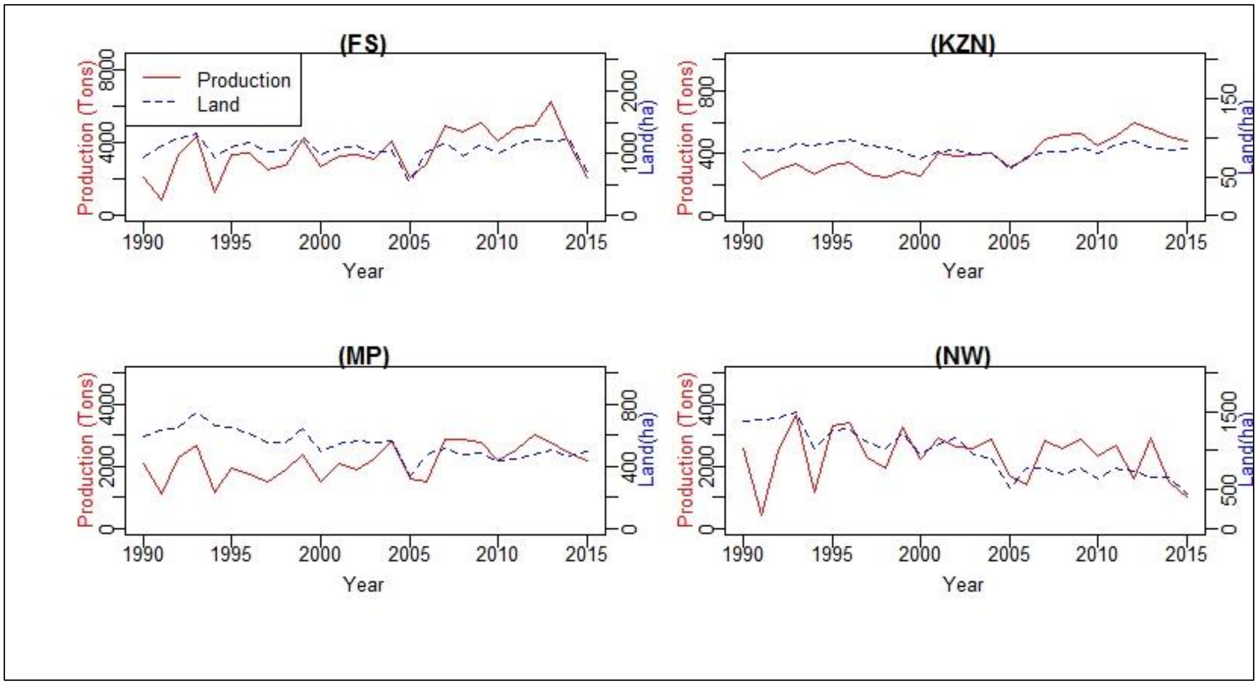

Figure 5-3: Plot of time series of maize production (tons) on the left y-axis (red line) and time series of cultivated land for maize (ha) (right y-axis) (dashed blue line) from 1990–2015 in FS: Free State, KZN: KwaZulu-Natal, MP: Mpumalanga and NW: North West provinces

5.2.2. Spatiotemporal variability of agrometeorological parameters and drought indices across the study area

A declining trend was observed for precipitation during the critical period of maize phenology across all the provinces. The results revealed that 97% (26) of the stations had decreasing precipitation during the main maize growth stages (-1.6 to -28.5 mm·decade^{-1}). About 15 out of 27 stations exhibited a decreasing trend in rainfall amount ($p < 0.05$). Five of these stations (84, 85, 90, 91 and 92) are located in NW, 4 (60, 71, 72 and 83) in FS, 3 (25, 30 and 40) in KZN and 2 (33 and 62) in MP. The mean temperature increased by 0.14 ± 0.05 ◦C·decade^{-1} over the entire stations in the study area, during the maize growing period (October to April), with 97% of the stations showing significant warming trends ($p < 0.05$). On the other hand, the decline in PET is observed in over 95% of the stations during the main maize growing period ($p < 0.05$). Positive values of the water balance (BAL) are observed in the month of December and January, indicating that the two months receive the largest rainfall months and are relatively moist.

The long-term spatially-averaged variation of the SPI and SPEI values 1-, 3-, 6- and 12-month periods across the main maize producing province are presented in Figs. 4, 5, 6 and 7. Only selected SPI and SPEI figures (for MP and FS) are presented here, the rest of the figures are provided as supplementary files. Homogeneity test of the SPI and SPEI values revealed significant differences between the two indices particularly the SPI/SPEI calculated at 3- to 12-month timescales. The correlation between the SPI and SPEI varies significantly across the different series. In particular, there is high correlation between the SPI and SPEI series within similar timescales (e.g. SPI-1: SPEI-1 (0.97), SPI-3: SPEI-3 (0.83), SPI-6: SPEI-6 (0.77), SPI-12: SPEI-12 (0.69)).

As indicated from the averaged SPI and SPEI across each province (Figs. 4, 5, 6 and 7), notable years of droughts include 1991/92, 1994/95, 2002/03, 2004/05, 2006/07, 2008/09, 2009/10, 2011/12 and 2014/15. Using the drought category in Table 1, 1991/92 and 2015/16 seasons are detected as the worst drought periods, reaching severe to extreme conditions. These drought epochs were generally reported to have negative impacts on livestock and crops (Vogel et al., 2000).

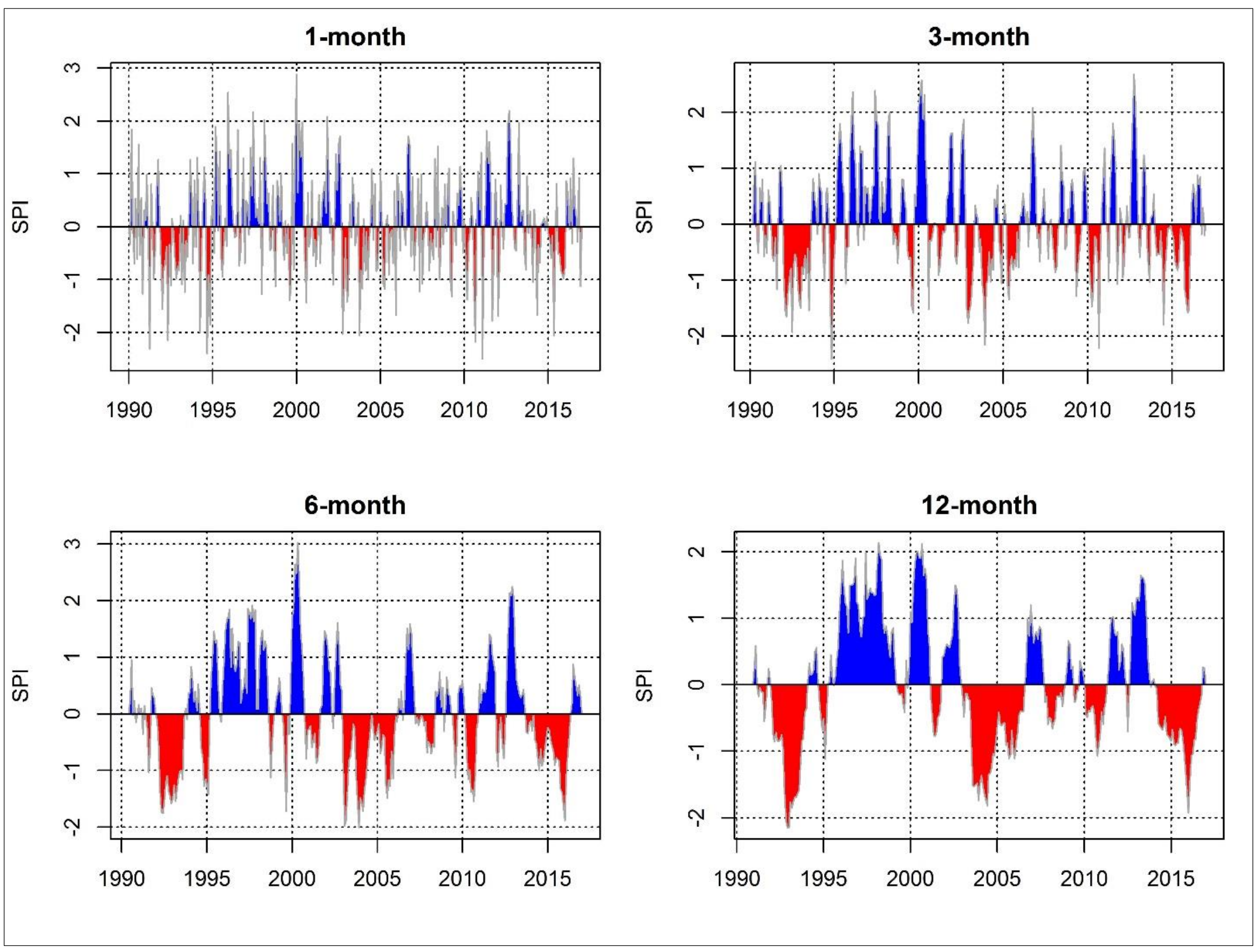

Figure 5-4: Drought indices quantified by the SPI at different timescales 1-, 3-, 6- and 12-month calculated using averages over the 4 stations in Mpumalanga province

Furthermore, the results indicate that there were moderate to extreme drought conditions during the maize growing period (October to April) across all the four provinces, but with inherent variation in the drought duration and severity. Moderate drought conditions dominated in MP, throughout the period. Severe drought occurred during 1991/92 and 2015/16, probably leading to widespread loss of livestock and summer agricultural production (Vogel et al., 2000). Furthermore, as shown by the 1-month drought period of the SPEI, moderate droughts are noticed with high frequency during the vegetative stage, considering planting dates as October across all the provinces. However, the moderate drought during the vegetative stage is more frequent in FS while NW province experiences more frequent extreme drought conditions (-1.00 to -1.49) during the vegetative stages, with a severe drought category in 1991/92 and 2014/15 (see supplementary file). On the other hand, the results depict severe drought conditions with high frequency and longer duration during the reproductive stages (3-month) in FS. The KZN province experienced moderate to severe drought in all the drought years identified, reaching an extreme drought condition category in 2015/16.

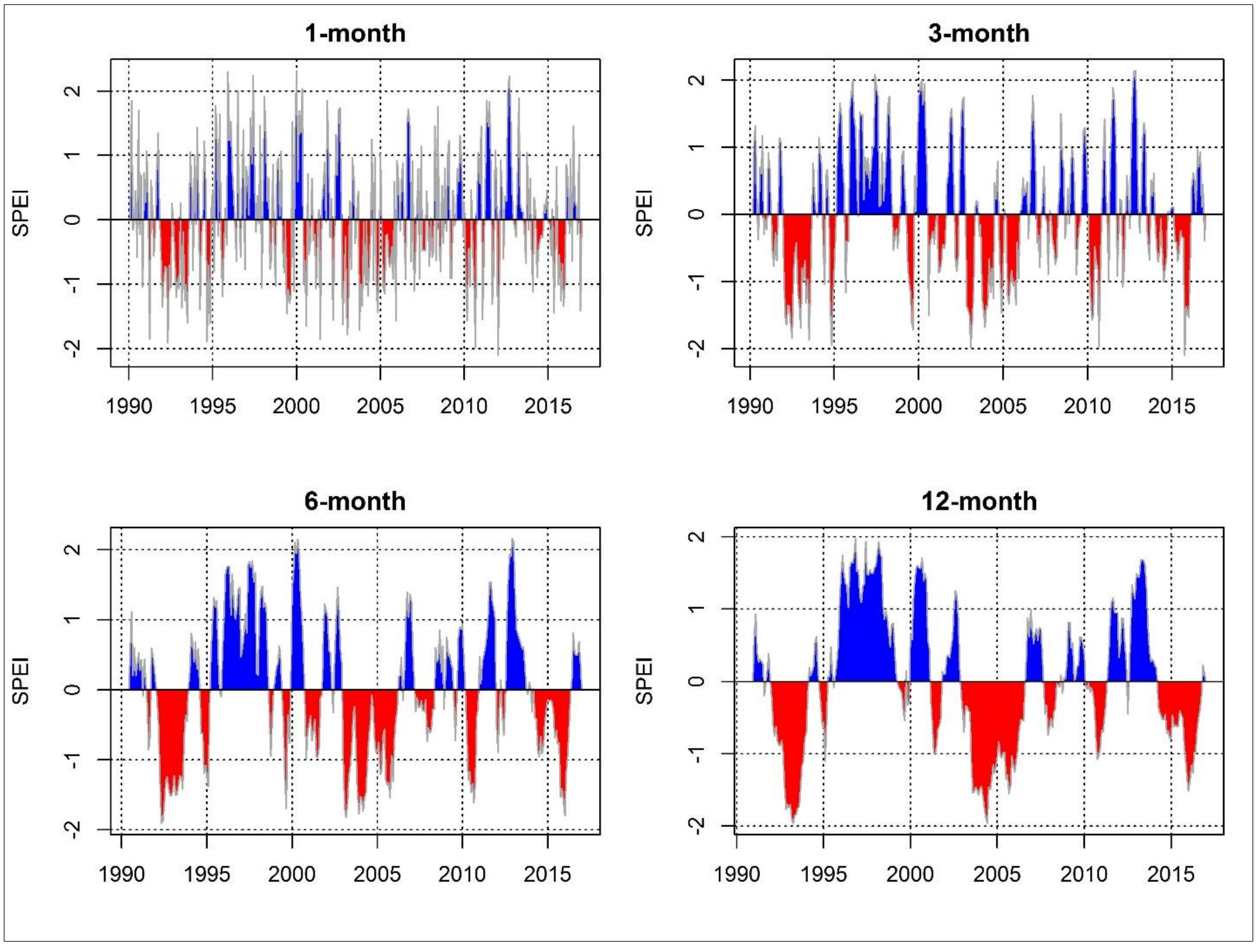

Figure 5-5: Drought indices quantified by the SPEI in different timescale 1-, 3-, 6- and 12-month calculated using the averages over the 4 stations in Mpumalanga province

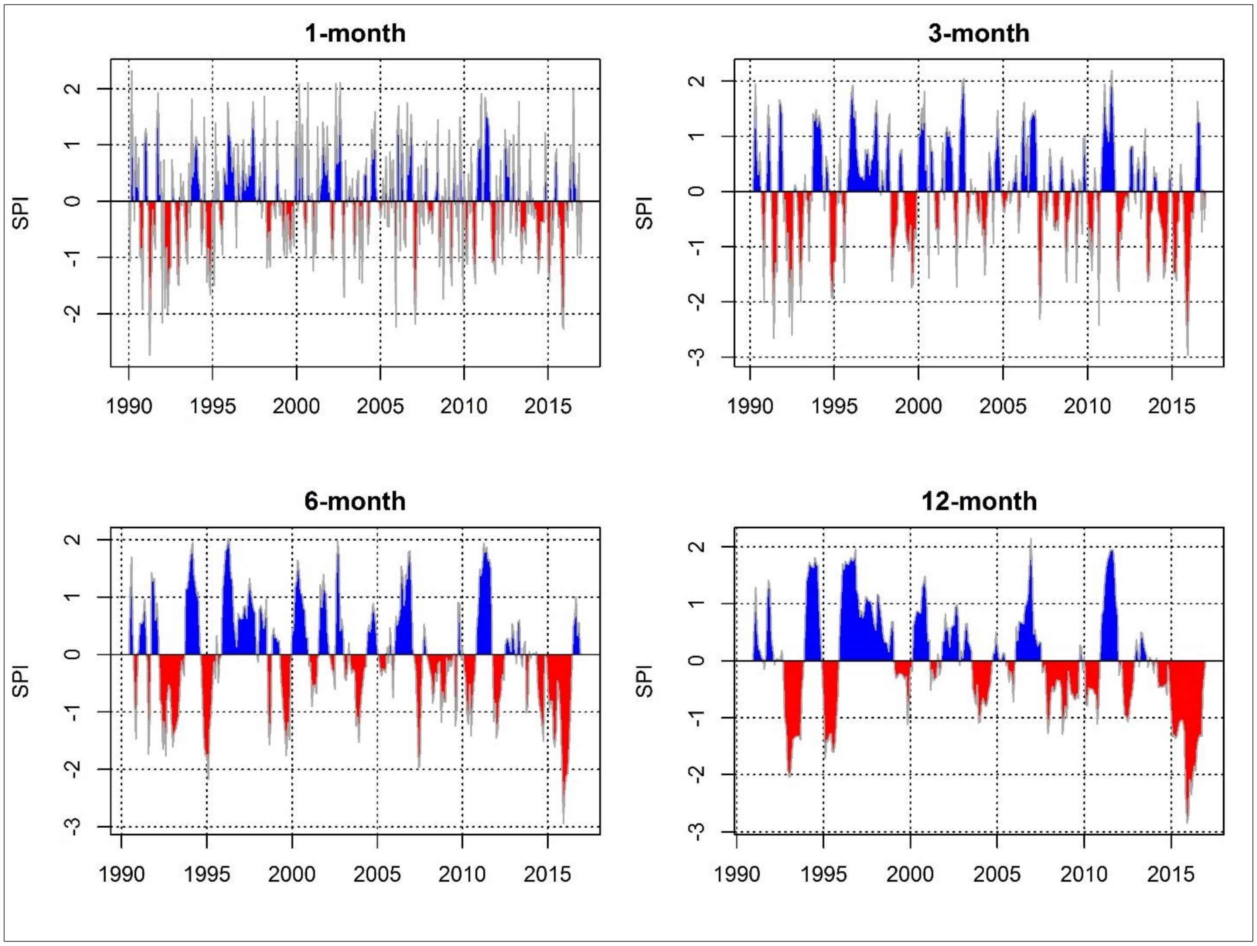

Figure 5-6: Drought indices quantified by the SPI in different timescale 1-, 3-, 6- and 12-month calculated using averages over the 9 stations in Free State province

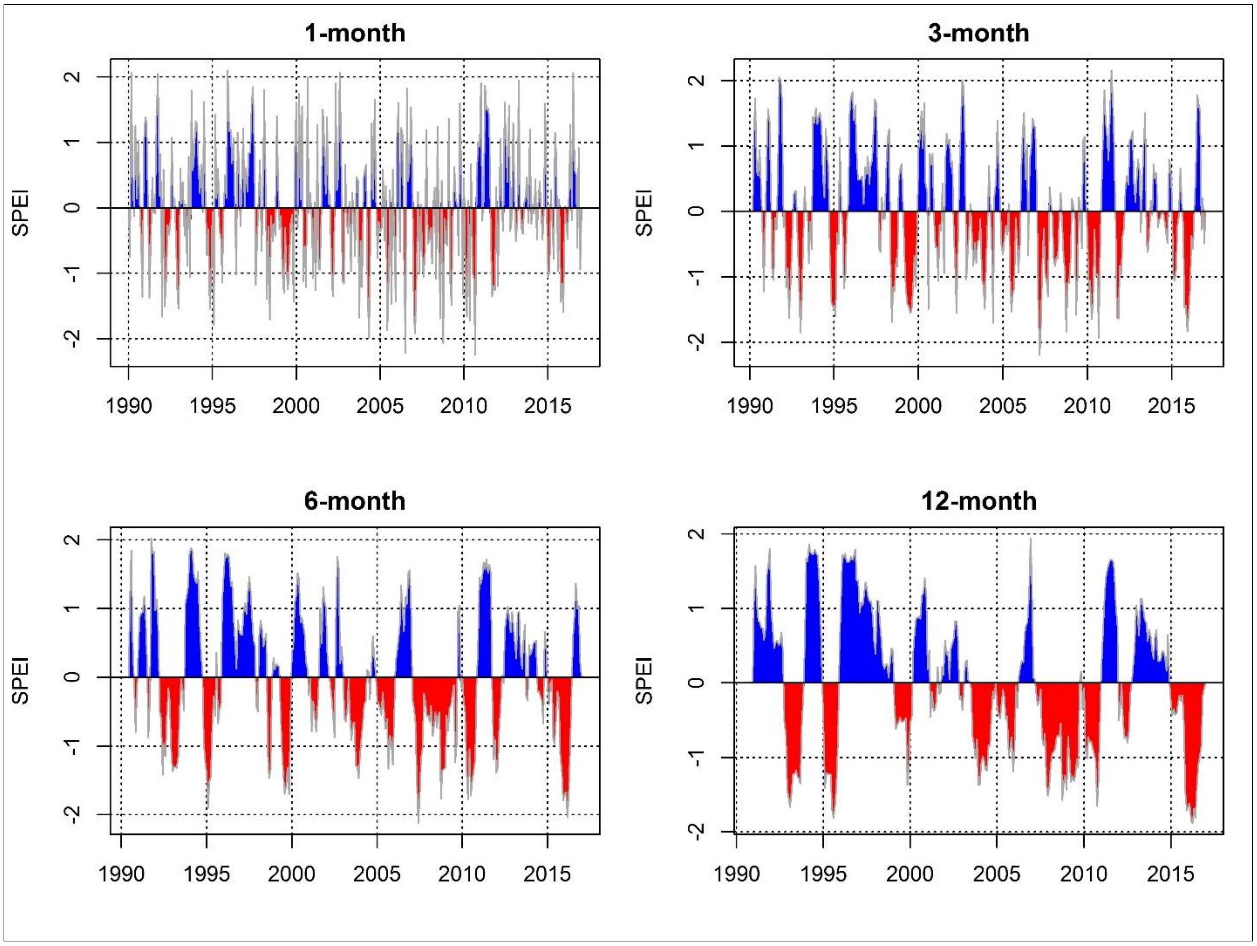

Figure 5-7: Drought indices quantified by the SPEI in different timescale 1-, 3-, 6- and 12-month using the averages over 9 stations in Free State province

The major drought years were confirmed by the breakpoints (Fig. 8) detected in SPI and SPEI time series. The horizontal black and blue lines represent the values and the trends of the SPI and SPEI respectively, while the vertical tick dotted lines are the breakpoints (significant change points in the time series). In particular, based on the SPI analysis major droughts occurred in 1991/92, 1994/95, 2004/05, 2006/07 and 2012/13. Based on the SPEI analysis, a major drought occurred in 1992/93, 1996/97, 2002/03, 2005/06 and 2007/08. These results confirm findings reported in the previous studies (e.g. Vogel *et al.*, 2000; Rouault and Richard, 2003), indicating that the indices are able to detect periods of significant droughts.

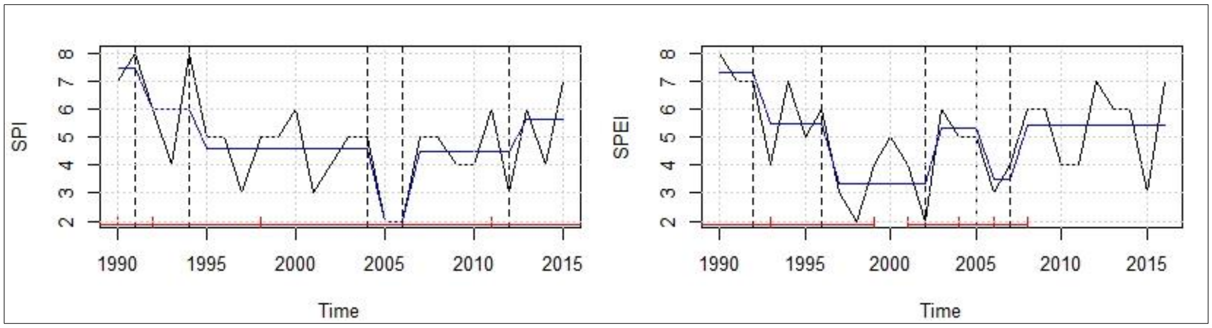

Figure 5-8: Breakpoints in SPI and SPEI time series showing the drought years which are detected with breakpoints in tick dotted lines

5.2.3. Spatial variability of drought conditions across the study area

In this study, drought conditions across the NW, FS, KZN and MP provinces were characterized based on DMIs such as DD, DS as well as CDM. Statistical parameters such as the mean, the coefficient of variation, and trends of the DMIs were derived from the SPI and SPEI time series. However, for easy readership, only the results for the SPI-3 and SPEI-3 which have higher correlations with maize yield as shown in Table 3 are given. The results for the DD, DS and CDM derived from the SPI-3 and SPEI 3-month are depicted in Fig. 9. As shown in Fig. 9, DD, mean values range between 4 and 6 months across the provinces. The mean of the DD is minimum towards the west-northern part of the NW province (SPI-3) and parts of the FS province (SPEI-3) and increases across the study region, reaching its maximum in regions of MP province (SPI-3) and FS (SPEI-3).

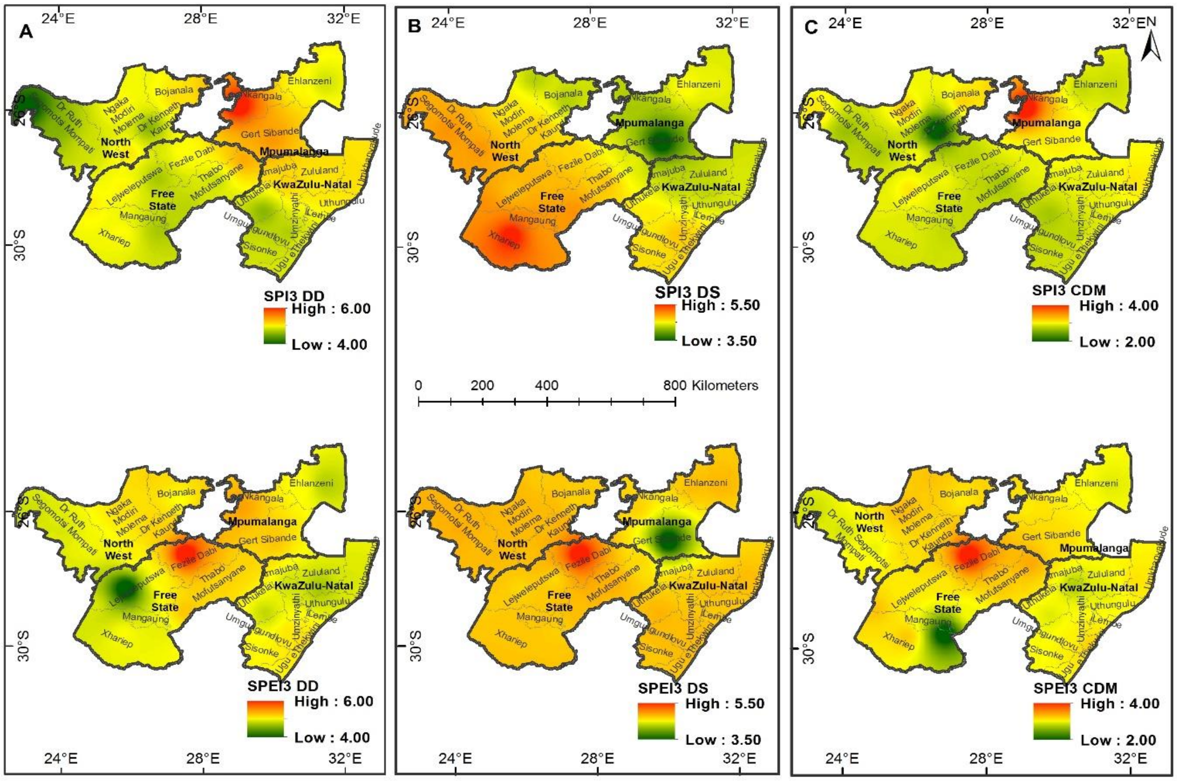

Figure 5-9: Spatial contrasts of the mean DMIs derived from SPI-3 (top) and SPEI-3 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM

Additionally, the mean values in the DS are lowest in the central region of MP for both SPI-3 and SPEI-3 and maximum in the FS province. On the other hand, the mean CDM values range between 2 and 4 months. Few parts of the MP province depict higher mean for SPI-3 while higher CDM mean is evident in the northern areas of FS province for SPEI-3. The results indicate that drought is more severe in both FS and NW provinces with longer duration in FS. While the drought conditions seem to be less severe in MP province, these conditions exhibit generally persistent characteristics across the province. Given that the SPI-3 and SPEI-3 values correspond to the reproductive stages of maize (averaged December-January) from silking to grain-filling from 61st to 90th day, these drought conditions will, therefore, have a huge negative impact on the overall maize production. Note that the study area comprises of the main maize producing areas. These severe and persistent drought conditions inherently threaten the economy and the food security of the country.

The spatial contrasts of the CV results derived from the SPI-3 and SPEI-3 time series are illustrated in Fig. 10. Based on the SPI-3 analysis, the NW province depicts less variability in DD. Similar results are observed for DD derived from the SPEI-3, although few regions in the FS depict maximum CV values (~40%). The CV values derived from the SPI-3 time series exhibit subtle variation mostly in KZN and highly dispersed in the FS province. For SPEI-3 analysis, the CV values in DS range between ~28% (mostly in KZN) and ~40% (mostly in FS and MP). Based on both the SPI-3 and SPEI-3 time series analysis, vast majority of the study area depicts variations of CV values in CDM, with maximum values of ~55% and ~54% for SPI-3 and SPEI-3, respectively.

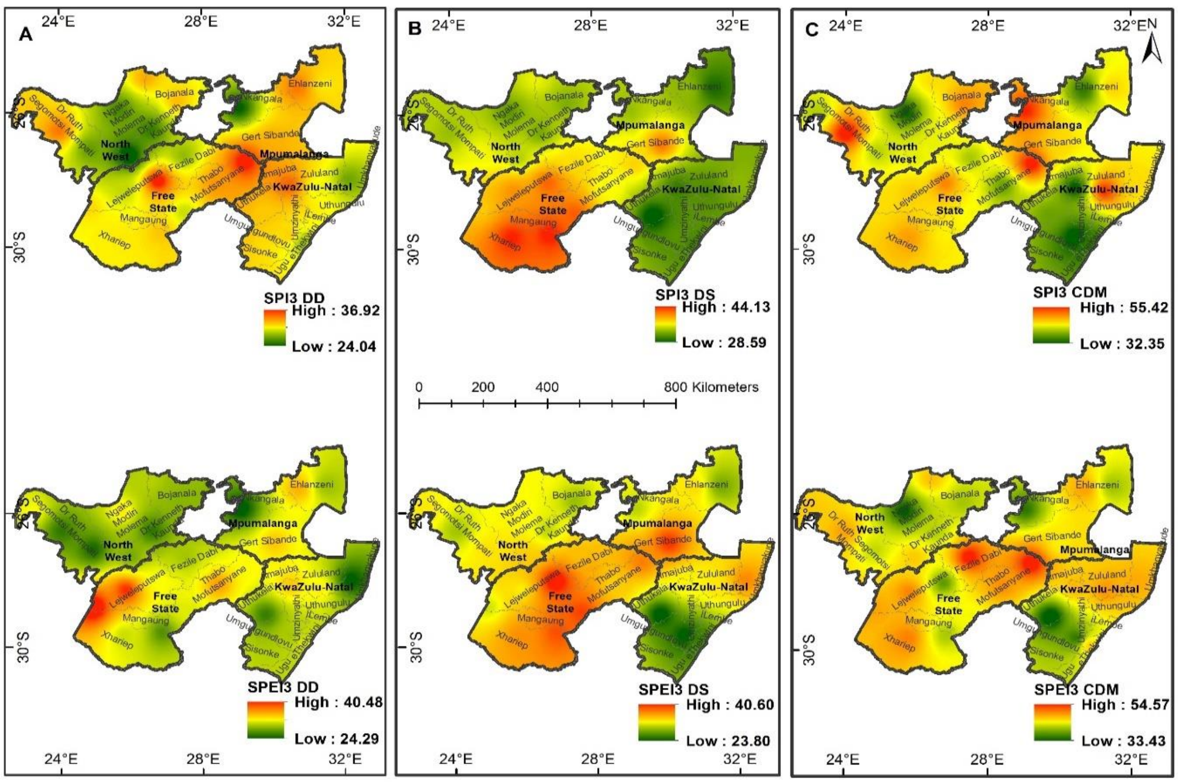

Figure 5-10: Spatial contrasts of the coefficient of variation (CV) of DMIs derived from SPI-3 (top) and SPEI-3 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM

The results of spatial-temporal trends in DD, DS and CDM, calculated from SPI- and SPEI- 3-month timescales are depicted in Fig. 11 and their significance (p-values) shown in Fig. 12. Similar trend pattern in DD is observed for both SPI-3 and SPEI-3. In particular, the trends in DD range between -0.05 and 0.04 for the SPI-3 and -0.05 and 0.04 for the SPEI-3 time series. Subtle negative trends in the DD are observed mainly in the KZN province for both SPI-3 and SPEI-3. On the other hand, trivial positive trends are observed in the DS over large parts of the NW, FS, and some regions in the south-western parts of the MP province. As shown in Fig. 11, no detectable trends in CDM are observed for both SPI-3 and SPEI-3 time series, across the study area, except for a small region in the NW province that depicts subtle negative trends with a minimum of -0.02 month/year. Overall, the derived trends for the drought indicators across the selected timescales are mostly found to be statistically insignificant at 0.05. However, a fraction of trends in DS are found to be statistically significant in NW and KZN (see Fig. 11).

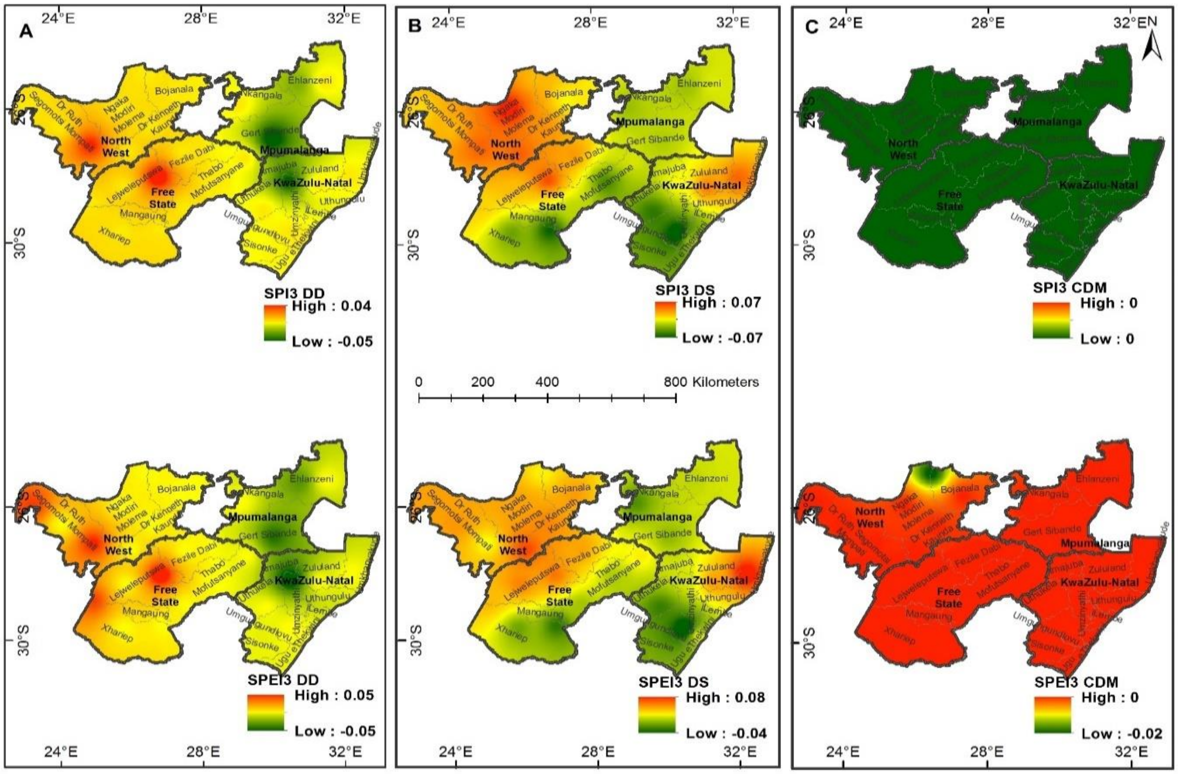

Figure 5-11: Spatial contrasts of the trends of DMIs derived from SPI-3 (top) and SPEI-3 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM

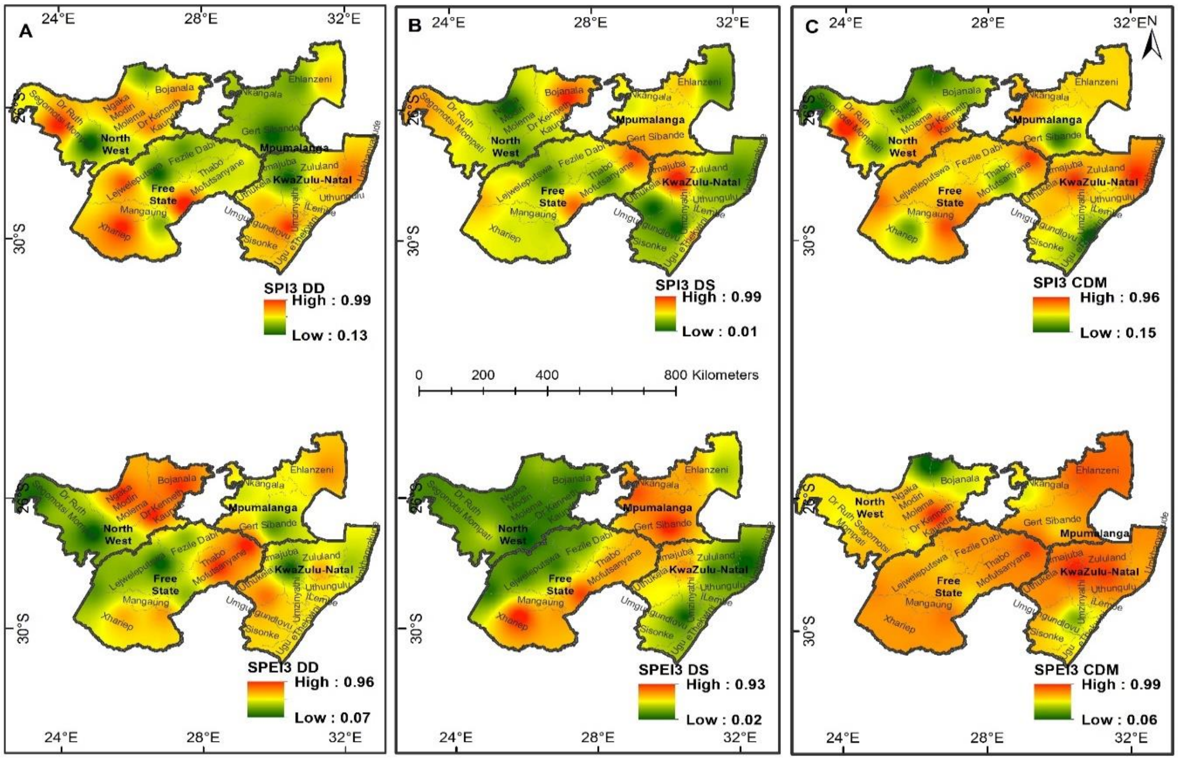

Figure 5-12: Spatial contrasts of the p-values of DMIs derived from SPI-3 (top) and SPEI-3 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM

5.2.4. Impacts of drought on the maize yield

Table 3 shows the results of the correlation analysis between drought indices and maize yield across the provinces. The highest correlation was observed between the SPEI-3 and maize yield across all the provinces except for KZN where the SPI-3 has the highest correlation.

Table 5-3: Correlation coefficients of the SPI and SPEI 1-, 3-, 6- and 12 months series (October to April), and the standardized maize yield in major four maize producing provinces of South Africa from 1990-2015

				SPI				
Province	**SPI-1**	**p-value**	**SPI-3**	**p-value**	**SPI-6**	**p-value**	**SPI-12**	**p-value**
KZN	0.58	0.038	0.67	0.014	0.41	0.067	0.18	0.517
MP	0.53	0.044	0.56	0.032	0.32	0.132	0.21	0.445
FS	0.34	0.167	0.51	0.051	0.29	0.217	0.27	0.267
NW	0.48	0.101	0.53	0.045	0.33	0.093	0.26	0.189
				SPEI				
Province	**SPEI-1**	**p-value**	**SPEI-3**	**p-value**	**SPEI-6**	**p-value**	**SPEI-12**	**p-value**
KZN	0.43	0.081	0.47	0.049	0.39	0.053	0.20	0.523
MP	0.52	0.049	0.58	0.041	0.42	0.062	0.22	0.334
FS	0.60	0.041	0.62	0.035	0.56	0.047	0.31	0.114
NW	0.59	0.026	0.69	0.011	0.53	0.058	0.32	0.105

The correlation results given in Table 3 suggest that SPEI-3 is the most sensitive drought indicator to maize yield having correlation (r = 0.69, 0.62, 0.58; $p < 0.05$ in NW, FS and MP respectively) and SPI-3 (r = 0.67, $p < 0.05$) in KZN. The results further indicate that the SPEI-3 is able to explain about 48%, 39% and 34% of maize yield variation in NW, FS, and MP respectively, while the SPI-3 is able to explain about 45% of the variation in maize yield in KZN. The results suggest that the SPEI, which takes PET into account, can better estimate the impact of drought on maize yield in MP, FS, and NW while the SPI shows a better evaluation of the impact of drought on maize yield in KZN. These results are consistent with the findings of Zipper *et al.* (2016) and Kurniasih and Impron (2017) who reported that crops yield such as maize and soybean are most responsive to short-term (1–3 month) period. Similarly, Bachmair *et al.* (2018) reported that the SPI-3-month timescale was best suited for monitoring the effects of drought in agriculture and forestry. Furthermore, the results are also consistent with previous studies by Adisa *et al.* (2018) where result of the Partial Least Square Path Modeling (PLS-PM) analysis indicated that the impact of climatic elements on phenological parameters and indirectly on maize yield varies across the provinces with 70%, 72%, 76% and 79% in Mpumalanga, KwaZulu-Natal, North West and Free State, respectively. The SPI-3 and SPEI-3 correspond with the critical reproductive stages of maize growing season (December-January) during silking and grain-filling (Aslam *et al.*, 2013). Drought occurrence during this stage could reduce the potential maize yield by up to 50% (Heiniger, 2001).

5.3. Discussion

For the effective policy support, social capital provision and adaptation of agricultural systems to climate change, it is essential to understand the impact of extreme climate conditions such as drought on agricultural production (Chen *et al.*, 2014). In this study, two commonly used drought indices; SPI and SPEI were analyzed at different timescales of 1-, 3-, 6- and 12-month in order to determine their relationship with changes in maize yield. The results depict large spatial variations in drought impacts in term of its duration, frequency and severity and the trend, with drought associated with an average of 35% of the variation in maize yield. Drought at 3-month timescale (particularly, December – January, a critical reproductive stage of the growing season) tends to be the dominant driver of maize yield variability. The reproductive stages are the most sensitive stages of maize, hence the duration and severity of drought during this stage can reduce the potential maize yield by up to 50% (Adisa *et al.*, 2018). The results confirm previous findings that drought at short timescales is more significant than longer timescale because the growth and performance of crop are more sensitive to short-term weather events that alter soil moisture conditions rapidly and substantially (Wu *et al.,* 2004). In this study, the SPI, a precipitation-based drought index, exhibits a lower correlation with maize yield across the provinces except in KZN. In addition, the SPEI estimates the drought-induced yield impact better than the SPI in warming weather conditions. The multi-scalar characteristics of SPEI enable it to identify different drought types and effects in the context of global warming (Ujeneza and Abiodun, 2015; Vicente-Serrano *et al.*, 2010).

Furthermore, the variation in the duration, frequency, and severity of the SPI and SPEI indices can be explained by the variation in the climate characteristics across the provinces. As reported by the previous studies (e.g. Kruger and Nxumalo, 2017; Adisa *et al.,* 2017; Botai *et al.*, 2018), there is a large variation in the amount of rainfall received across the province. The north-eastern part of the country is often drier than the central, while the south-western part gets wetter. Furthermore, Kruger and Nxumalo (2017) reported that there is less amount of rainfall at the onset of rainfall, particularly in the FS province. Hence, drought conditions are more inherent in the northern (MP) and western-central (FS and NW) of the country. This could further explain the moderate drought observed in the FS province and extreme drought in the NW province during the vegetative stage. According to Das (2012), the intra-seasonal variability of rainfall could lead to a deficit in the uptake of the required amount of water by crops as a result of the reduction of moisture in the root zone.

5.4. Conclusions

This study analyzed the SPI and SPEI indices at 1-, 3-, 6- and 12-month timescales in order to characterize the variability of drought duration, severity and magnitude as well as to determine the index and time period that is more sensitive to maize yield fluctuations over the four major maize producing provinces of South Africa during the crop growing period. Upon analyzing the characteristics of the drought and their correlations to maize yield between 1990 and 2015, the following conclusions emerge from this study:

- Both the SPI and SPEI have the capacity to described drought severity, duration and intensity in the study area.
- Compared to other accumulation periods, SPEI-3 has the greatest influence on the variation in maize yield across the study area.

- Drought conditions epochs between 1990 and 2015 exhibit a clear spatial-temporal dependence structure which manifests in the overall marginal maize production.
- Drought impacts on maize yield depend on drought magnitude and duration and on plant growth stages when droughts occur. Drought events during maize reproductive and vegetative stages cause the highest reduction in maize yield.
- The reduced maize yield during the notable drought years (1991/92, 1994/95, 2002/03, 2004/05, 2006/07, 2008/09, 2009/10, 2011/12 and 2014/15) could be attributed to the low rainfall amount during the growing season in some parts of the NW province.
- There were persistent drought conditions occurring during the sensitive growing stages of maize in some parts of KZN and MP provinces.

Overall, the present study contributes to the theoretical body of knowledge on droughts especially under changing climate. Results of this work could contribute towards the design of drought preparedness plans in a bid to manage future anticipated drought impacts in South Africa. One important area that the Agro-meteorology community need to carefully consider is whether the salient features of the Fourth Industrial Revolution have been harnessed at the appropriate level and pace given that the drought conditions and other weather and climate extremes are a threat to food security, the economies as well as the society. For further studies, the social aspect should be included so as to access the effect of drought on the economy of the farmers. Also, research of drought impact on maize production at farm level is highly recommended. The lack of the social aspect and data at the farm level are limitations but will be ideal for future studies in order to develop an effective climate mitigation and adaptation strategies.

Author Contributions: OMA conceptualised the research. AMA, CMB and ATA collected and cleaned the data. OMA, JOB and AMA analyzed the data and drafted the paper. DD, AH, ET, AFA and ATA reviewed the manuscript. All authors read and approved the paper submission for publication.

Funding: This research received no external funding.

Acknowledgments: The authors gratefully acknowledge financial support from the Department of Science and Technology (DST) and The National Research Foundation (NRF).

Conflicts of Interest: The authors declare no conflicts of interest.

References

Adisa OM, Botai CM, Botai JO, Hassen A, Darkey D, Tesfamariam E, Adisa AF, Adeola AM, Ncongwane KP, 2017: Analysis of agro-climatic parameters and their influence on maize production in South Africa. *Theoretical and. Applied Climatology* **134**, 991–1004.

Adisa OM, Botai JO, Hassen A, Darkey D, Adeola AM, Tesfamariam E, Botai CM, Adisa AT, 2018: Variability of satellite-derived phenological parameters across maize producing areas of South Africa. *Sustainability* **10**, 3033; doi:10.3390/su10093033.

Ali MG, Younes K, Esmaeil A, Fatemeh T, 2011: Assessment of geostatistical methods for spatial analysis of SPI and EDI drought indices. *World Applied Sciences Journal* **15**, 474-482.

Allen RG, Pereira LS, Raes D, Smith M, 1998: *Crop Evapotranspiration: Guidelines for Computing Crop Requirements, Irrigation and Drainage* Paper **56**. Roma, Italia: FAO.

Aslam M, Zamir MSI, Afzai I, Yaseen M, Mubeen M, Shoaib A, 2013: Drought stress, its effect on maize production and development of drought tolerance through potassium application. *Agronomical Research in Moldavia* **2**, 99-114.

Bachmair S, Tanguy M, Hannaford J, Stahl K, 2018: How well do meteorological indicators represent agricultural and forest drought across Europe? *Environmental Research Letters* **13**, 34-42.

Beguería S, Vicente-Serrano SM, 2013: SPEI: Calculation of the standardised precipitation-evapotranspiration index. R package. Available online: https://CRAN.R-project.org/package=SPEI (accessed on 1 May 2018).

Botai CM, Botai JO, Adeola AM, 2018: Spatial distribution of temporal precipitation contrasts in South Africa. *South African Journal of Science* **114**, 1-9.

Botai CM, Botai JO, de Wit JC, Ncongwane KP, Adeola AM, 2017: Drought characteristics over the Western Cape Province, South Africa. *Water* **9**, doi:10.3390/w9110876.

Botai CM, Botai JO, Dlamini LC, Zwane NS, Phaduli E, 2016: Characteristics of droughts in South Africa: A Case Study of Free State and North West Provinces. *Water* **8**, doi:10.3390/w8100439.

Byun H, Wilhite DA, 1999: Objective quantification of drought severity and duration. *Journal of Climate* **12**, 2747-2756.

Byun HR, Kim DW, 2010: Comparing the effective drought index and the standardized precipitation index. In: López-Francos A. (comp.), López-Francos A. (collab.). Economics of drought and drought preparedness in a climate change context. Zaragoza: CIHEAM / FAO / ICARDA / GDAR / CEIGRAM / MARM, pp. 85-89.

Ceglar B, Medved-Cvikl E, Moran-Tejeda S, Vicente-Serrano L, Kajfež-Bogataj, 2012: Assessment of multi-scale drought datasets to quantify drought severity and impacts in agriculture: a case study for Slovenia. *International Journal of Spatial Data Infrastructures Research* **7**, 464-487.

Chen H, Fan L, Wu W, Liu HB, 2017: Comparison of spatial interpolation methods for soil moisture and its application for monitoring drought. *Environmental Monitoring and Assessment* **189**, doi:10.1007/s10661-017-6244-4.

Chen H, Wang J, Huang J, 2014: Policy support, social capital, and farmers' adaptation to drought in China. *Global Environmental Change* **24**, 193-202.

Chen T, van der Werf GR, de Jeu RAM, Wang G, Dolman AJ, 2013: A global analysis of the impact of drought on net primary productivity. *Hydrology and Earth System Sciences* **17**, 3885–3894.

Chen T, Xia G, Liu T, Chen W, Chi D, 2016: Assessment of drought impact on main cereal crops using a standardized precipitation evapotranspiration index in Liaoning Province, China, *Sustainability* **8**, 1069, doi:10.3390/su8101069.

Dalezios N, Blanta A, Spyropoulos N, Tarquis A, 2014: Risk identification of agricultural drought for sustainable agroecosystems. *Natural Hazards and Earth system Science* **14**, 2435-2448.

Das HP, 2012: *Agrometeorology in extreme events and natural disasters*. BS Publications, India, pp 600.

DAFF (Department of Agriculture, Forestry and Fisheries). Trends in the Agricultural Sector 2017. Pretoria. Available online: https://www.daff.gov.za/Daffweb3/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Trends%20in%20the%20Agricultural%20Sector%202017.pdf (Accessed 29 May 2018).

Dutta D, Kundu A, Patel NR, Saha SK, Siddiqui AR, 2015: Assessment of agricultural drought in Rajasthan (India) using remote sensing derived vegetation condition index (VCI) and Standardized Precipitation Index (SPI). *The Egyptian Journal of Remote Sensing and Space Sciences* **18**, 53-63

Edossa DC, Woyessa YE, Welderufael WA, 2014: Analysis of droughts in the central region of South Africa and their association with SST anomalies. *International Journal of Atmospheric Sciences* **2014**, 1-8.

Grayson M, 2013: Agriculture and drought. *Nature* **501**, doi:10.1038/501S1a

Heiniger RW, 2001: The impact of early drought on corn yield. **2001**, Available at http://www.agrigold.com/Universal/Articles/The-Effects-on-Drought-on-Corn-Yield/ (Accessed 11 June 2018).

Hollinger SE, Isard SA, Welford MR, 1993: A new soil moisture drought index for predicting crop yields. *In proceedings of the 8th conference on applied climatology*. Anaheim, CA, USA, 17-22 January, pp. 187-190.

IPCC Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; *Cambridge University Press*: Cambridge, UK; New York, NY, USA.

Kruger AC, Nxumalo MP, 2017: Historical rainfall trends in South Africa: 1921-2015. *Water South Africa* **43**, 285-297.

Kurniasih E, Impron P, 2017: Use of drought index and crop modelling for drought impacts analysis on maize (Zea mays L.) yield loss in Bandung district. IOP Conf. Series: *Earth and Environmental Science* **58,** 12-36.

Mansouri DMR, Bagherzadeh A, Khosravi M, 2013: Assessment of drought hazard impact on wheat cultivation using standardized precipitation index in Iran. *Arabian Journal of Geosciences* **11**, 4463-4473.

Marchetto A, 2017: rkt: Mann-Kendall test, seasonal and regional kendall tests. Available online: https://CRAN.R-project.org/package=rkt (accessed on 1 May 2018).

Masupha TE, Moeletsi ME, 2017: Use of standardized precipitation evapotranspiration index to investigate drought relative to maize, in the Luvuvhu River catchment area, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C*. **92**, 1-9.

McKee TB, Doesken NJ, Kleist J, 1993: The relationship of drought frequency and duration to time scales. *In proceedings of the 8th conference on applied climatology*, Anaheim, CA, USA, 17-22 January, pp. 179-184.

Meroni M, Rembold F, Fasbender D, Vrieling A, 2017: Evaluation of the standardized precipitation index as an early predictor of seasonal vegetation production anomalies in the Sahel, *Remote Sensing Letters* **8**, 301-310, doi:10.1080/2150704X.2016.1264020.

Morid S, Smakhtin V, Moghaddasi M, 2006: Comparison of seven meteorological indices for drought monitoring in Iran. *International Journal of Climatology* **26**, 971-985.

Palmer WC, 1968: Keeping track of crop moisture conditions, nationwide: the new crop moisture index. *Weatherwise* **21**, 156-161.

Pannar, 2012: Quality seed, know the maize plant. Pannar Seeds, Private Limited

Potop, V.; Možný, M.; Soukup, J. Drought at various time scales in the lowland regions and their impact on vegetable crops in the Czech Republic. Agr. For. Meteorol. 2012, 156, 121–133.

Potop V, Boroneat C, Možný M, Štˇepánek P, Skalák P, 2014: Observed spatio-temporal characteristics of drought on various time scales over the Czech Republic. *Theoretical and Applied Climatology* **112**, 3-11.

Potopová V, Boroneant C, Boincean B, Soukup J, 2016: Impact of agricultural drought on main crop yields in the Republic of Moldova. *International Journal of Climatology* **36**, 2063-2082.

Potopová V, Štěpánek P, Možný M, Türkott L, Soukup J, 2015: Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. *Agricultural and Forest Meteorology* **202**, 26-38.

Rhee J, Carbone GJ, Hussey J (2008) Drought index mapping at

different spatial units. J Hydrometeorol 9(6):1523–1534

Rhee J, Carbone GJ, Hussey J (2008) Drought index mapping at

different spatial units. J Hydrometeorol 9(6):1523–1534

Rhee J, Carbone GJ, Hussey J, 2008: Drought index mapping at different spatial units. *Journal of Hydrometeorology* **9**, 1523–1534.

Rouault M, Richard Y, 2003: Intensity and spatial extension of drought in South Africa at different time scales. *Water South Africa* **4**, 489-500.

Thornthwaite CW, 1948: An approach toward a rational classification of climate. *Geographical Review* **38**, 55-94.

Tsakiris G, Vangelis H, 2005: Establishing a drought index incorporating evapotranspiration. *European Water* **9**, 3-11.

Ujeneza EL, Abiodun BJ, 2015: Drought regimes in Southern Africa and how well GCMs simulate them. *Climate Dynamics* **44**, 1595–1609.

Vasiliades L, Loukas A, 2013: An operational drought monitoring system using spatial interpolation methods for Pinios river basin, Greece. *Proceedings of the 13th International Conference on Environmental Science and Technology*. Athens, Greece, 5-7 September 2013

Vicente-Serrano SM, Beguería S, López-Moreno JI, 2010: A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate* **23**, 1696-1718.

Vicente-Serrano SM, Beguería S, Lorenzo-Lacruz J, Camarero JJ, López-Moreno JI, Azorin-Molina C, Revuelto J, Morán-Tejeda E, Sanchez-Lorenzo A, 2012: Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interactions* **16**, 1-27.

Vicente-Serrano SM, Sergio M, and National Center for Atmospheric Research Staff, 2015: The climate data guide: standardized precipitation evapotranspiration index (SPEI). Available at: https://climatedataguide.ucar.edu/climatedata/standardizedprecipitationevapotranspiration-index-spei (Accessed on 15 April 2016).

Vogel C, Laing M, Monnik K, 2000: Drought in South Africa, with spatial reference to the 1980-94 period. In Wilhite, D.A. (Ed), Drought: A global assessment. *Routledge*, England pp. 348-366.

Wilhite DA, 1992: Preparing for Drought: A guidebook for developing countries, climate unit, United Nations Environment Program, Nairobi, Kenya.

Wilhite DA, 2000: Drought: A global assessment, *Routledge*, New York, **1**, 89-104.

Woli P, Jones J, Ingram K, Paz J, 2013: Forecasting drought using the agricultural reference index for drought (arid): A case study. *Weather and Forecasting* **28**, 427-443.

Wu H, Hubbard KG, Wilhite DA, 2004: An agricultural drought risk-assessment model for corn and soybeans. *International Journal of Climatology* **24**, 723-741.

Yang M, Yan D, Yu Y, Yang Z, 2015: SPEI-based spatiotemporal analysis of drought in haihe river basin from 1961 to 2010. *Advances in. Meteorology* **2016** (Article ID 7658015)

Yue S, Pilon P, Phinney B, Cavadias G, 2002: The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological Processes* **16**, 1807-1829.

Zdeněk Z, Petr H, Karel P, Daniela S, Jan B, Miroslav T, 2017: Impacts of water availability and drought on maize yield-A comparison of 16 indicators. *Agricultural Water Management* **188,** 126-135.

Zhang Q, Zhang J, 2016: Drought hazard assessment in typical corn cultivated areas of China at present and potential climate change. *Natural Hazards* **81**, 1323-1331.

Zipper CS, Qiu J, Kucharik JC, 2016: Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. *Environmental Research Letters* **11**, doi:10.1088/1748-9326/11/9/094021.

Chapter 6

PREDICTING MAIZE USING NEUTRAL-NETWORK ANALYSIS

Application of Artificial Neural Network for Predicting Maize Production in South Africa

Omolola M. Adisa [1,*], Joel O. Botai [1,2,3], Abiodun M. Adeola [2,4], Abubeker Hassen [5], Christina M. Botai [2], Daniel Darkey [1], and Eyob Tesfamariam [6]

[1] Department of Geography, Geoinformatics & Meteorology, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; lolaadisa@yahoo.com (O.M.A); daniel.darkey@up.ac.za (D.D.)

[2] South African Weather Service, Private Bag X097, Pretoria 0001; joel.botai@weathersa.co.za (J.B.); abiodun.adeola@weathersa.co.za (A.A.); christina.botai@weathersa.co.za (C.B.)

[3] School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Westville Campus, Private Bag X54001, Durban 4000, South Africa

[4] School of Health Systems and Public Health, Faculty of Health Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa

[5] Department of Animal and Wildlife Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; abubeker.hassen@up.ac.za (A.H.)

[6] Department of Plant and Soil Sciences, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; eyob.tesfamariam@up.ac.za (E.T.)

***** Correspondence: u13387562@tuks.co.za

Received: 22 December 2018; Accepted: 19 February 2019; Published: 21 February 2019

This article has been published in Sustainability, **2019**, *11*(4), 1145; https://www.mdpi.com/2071-1050/11/4/1145/pdf

Abstract: The use of crop modeling as a decision tool by farmers and other decision-makers in the agricultural sector to improve production efficiency has been on the increase. In this study, artificial neural network (ANN) models were used for predicting maize in the major maize producing provinces of South Africa. The maize production prediction and projection analysis were carried out using the following climate variables: precipitation (PRE), maximum temperature (TMX), minimum temperature (TMN), potential evapotranspiration (PET), soil moisture (SM) and land cultivated (Land) for maize. The analyzed datasets spanned from 1990 to 2017 and were divided into two segments with 80% used for model training and the remaining 20% for testing. The results indicated that PET, PRE, TMN, TMX, Land, and SM with two hidden neurons of vector (5,8) were the best combination to predict maize production in the Free State province, whereas the TMN, TMX, PET, PRE, SM and Land with vector (7,8) were the best combination for predicting maize in KwaZulu-Natal province. In addition, the TMN, SM and Land and TMN, TMX, SM and Land with vector (3,4) were the best combination for maize predicting in the North West and Mpumalanga provinces, respectively. The comparison between the actual and predicted maize production using the testing data indicated performance accuracy adjusted R^2 of 0.75 for Free State, 0.67 for North West, 0.86 for Mpumalanga and 0.82 for KwaZulu-Natal. Furthermore, a decline in the projected maize production was observed across all the selected provinces (except the Free State province) from 2018 to 2019. Thus, the developed model can help to enhance the decision making process of the farmers and policymakers.

Keywords: Maize; climate; prediction; artificial intelligence

---

6.0. Introduction

Agriculture is considered the most vulnerable sector to yearly climate change and variability, with the greatest impact on agricultural production [1]. Up to 30% yearly variations in the growing season of most commonly grown crops are attributed to meteorological conditions, including changes in precipitation and temperature variables [2,3]. Other factors known to affect crop yields include soil conditions [4], topography (elevation, slope, and aspect) [5], and socio-economic factors [6]. Crop modeling plays a significant role in agricultural production. Farmers and other decision makers in agriculture require precise crop yield prediction methods for better planning and decision-making [7]. In particular, crop yield predictions can assist farmers in deciding on seasonal crop planning and scheduling [8], as well as determining the possible future outcome of an event.

Yield prediction methods reported in literature include, regression, simulation, expert systems, and artificial neural network (ANN). Regression models have been widely used in various studies particularly for prediction purposes [9,10]. These could be attributed to the fact that they are easy to use and often produce reliable standard tests [11]. The use of regression models is sometimes limited, especially in complex cases like extreme data values and non-linear relationships. Furthermore, regression models might be inefficient because they do not always fulfill the regression assumptions for multiple co-linearity between the dependent and independent variables [12,13]. Diversity of interrelated factors influencing crop production makes describing their associations via conventional methods difficult [13].

An advantage of the simulation method is its potential to specify relevant factors affecting yield. This allows researchers in different fields of interest to use the same sophisticated model based on physical relationships [14]. However, simulation requires considerable biophysical inputs that sometimes demand estimation instead of measurement. Also, in areas devoid of established sets of parameters, calibration could be quite time-consuming. In addition, expert systems are highly dependent on human expertise and sets of logical rules to characterize yield. However, these logical rules entail extensive communication with the experts and these rules are not readily automated and are highly subjectable and reliant on a certain set of input data [14].

The use of ANN often resolves the complex relations and strong nonlinearity between crop production and different interrelated predictor parameters. Such methods are easily automated, contain objective mathematical functions rather than subjective rules, display considerable accuracy for new conditions not denoted in the input data, do not involve pre-established physical relationships, and can be generated using readily available data. According to [15], the ANN are considered to be the best procedures for extracting information from imprecise and non-linear data. ANN techniques have turned out to be a very vital tool for a wide variety of applications across many disciplines, including crop production prediction. Thus, with varying levels of success, they have been used for maize yield prediction based on soil and weather data [16,17].

ANNs are computer programs designed to simulate just the way the human brain processes information. In other words, they are the digitized models of the human brain [18]. The ANN models are characterized by an initiation function, which uses interrelated information processing units to transform input into output. Knowledge is acquired through neural networks by detecting relationships and patterns in data. Raw input data is received by the first layer of the neural network where it is processed and then transferred to the hidden layers. The hidden layer then passes the information to the last layer where the output is produced. ANNs are trained through experience with suitable learning exemplars in like manner to human but not from programming. They learn from given information, with an identified outcome that optimizes its weights for a better prediction in circumstances where there is an unknown outcome.

Maize is considered to be the most important grain crop, a staple food for a large proportion of the population and a major input to animal feed in South Africa. In South Africa, maize is produced by both commercial and subsistence farmers and accounts for about 45% of the gross domestic product of the agricultural sector. About 8 million tons of maize grain is produced annually in the country under varying soil, terrain, and climatic conditions. Free State (FS), North West (NW), Mpumalanga (MP) and KwaZulu-Natal (KZN) are the major maize producing provinces in South Africa accounting for about 83% of the total national production. FS and NW provinces both contribute over 60%, followed by MP (~24%) and KZN (less than 5%) [19].

Furthermore, the Food and Agriculture Organization of the United Nations (FAO) has recently reported maize as the largest grain crop (in metric tons) produced in the world [20]. Therefore, in order to ensure food security for a rapidly growing population, in the face of climate variability, several studies have been conducted on maize ranging from climate influence on maize to yield predictions. To this end, numerous researchers across the globe have used ANNs to predict maize yield and have proven this method to be reliable. For instance, Maryland's corn and soybean were predicted by developing a feed-forward back-propagation ANN model using the rainfall and soil properties [21]. Similarly, [14] predicted maize yield at three scales in east-central Indiana, USA, with local crop-stage weather and yield data spanning from 1901 to 1996 using a fully connected back-propagation ANN together with regression models. In addition, [22] developed a feed-forward neural network to estimate the nonlinear relationship between soil parameters and crop yield. The results indicated a relatively high degree of accuracy for crop yield prediction. Furthermore, a study by [23] in eastern Ontario, Canada, evaluated the predicting power of ANN for corn and soybean yield using remotely sensed variables. The model was found to report an error level below 20% indicating the reliability of the model in predicting corn and soybean yield.

Using climate data and fertilizer as predictors, [24] predicted maize yield in Jilin, China. The authors reported a close similarity between the predicted yield and the observed yield. Despite proven reliability of the application of ANNs to maize yield production as shown in other countries, no study has been reported or published to have used these models for predicting maize yield in South Africa. Many of the existing studies have relied on the use of crop-based models which are in most cases expensive and data intensive. The aim of this study is to develop an artificial neural network for predicting maize yield in the major maize producing areas of South Africa (FS, NW, MP, and KZN).

6.1. Materials and Methods

6.1.1. Study Area

The study area includes the north-eastern part of South Africa between longitude 22°E to 33°E and latitude –32°S to –24°S. It covers KZN, FS, MP, and NW provinces, see Figure 1. Agriculture dominates the FS landscape. This is attributed to the fact that the province is agro-ecologically located on a flat plain with approximately 5% slopes. It is about 1300 m above sea level, characterized by summer rainfall (500–600 mm annually), temperature ranging between 1 °C to mild 17 °C in winter and 15 °C to 32 °C in summer. As the FS has more than 30,000 farmers producing over 70% of the country's grain, hence the province is referred to as the "Heart and Bread-Basket of the Country".

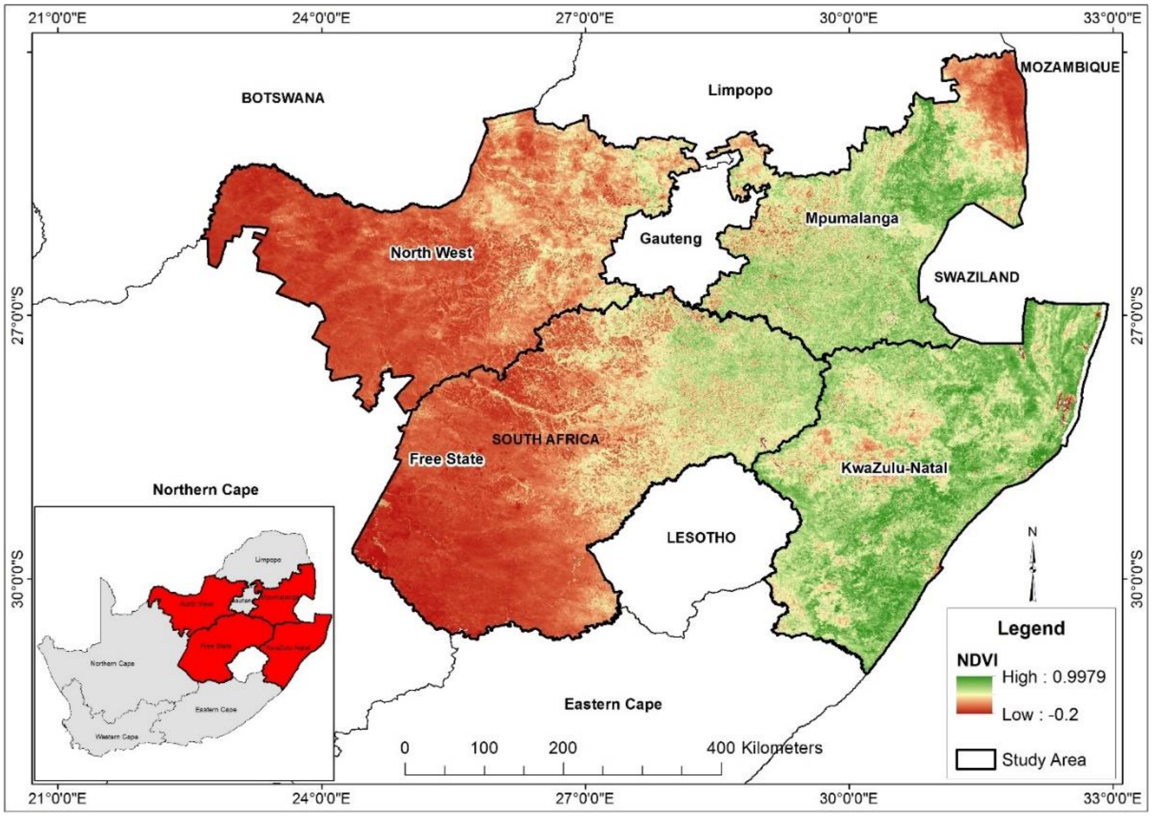

Figure 6-1: Map showing the geographic location of the study area; inset: The South Africa national boundary showing the location of the major maize producing provinces.

The NW province is considered to be an important contributor to the South Africa food basket with an estimated 43.9% of the province categorized as "arable" land. There are three distinct climatic regions which allow a wide variety of agricultural activity. The drier western region (hunting, cattle, and game farming), the central and southern parts (maize, wheat and cash crops) and the eastern and north-eastern region (variety of crops). The province is characterized by almost all year-round sunshine, rainfall ranges between 300 and 700 mm per annum, summer temperature ranging from 22 °C to 34 °C and winter temperature ranging from 2 °C to 34 °C. The MP province is rated as one of South Africa's most important and productive agricultural regions. The province is characterized by rainfall of about 500 reaching up to 800 mm per annum with an average temperature of about 19 °C. In KZN the land area devoted to grain and seed production varies yearly according to the price of crops, demand and supply, and annual rainfall received. The province is characterized by long, hot summer with temperature ranging from 23 °C to 33 °C, winter temperature ranging from 16 °C to 25 °C, and an average annual rainfall of 500 to 800 mm [25].

6.1.2. Datasets

The datasets used in this study are: the Normalized Difference Vegetation Index (NDVI), potential evapotranspiration (PET), precipitation (PRE), minimum temperature (TMN), maximum temperature (TMX), soil moisture (SM), size of land cultivated for maize production (Land) and maize production per province (P) as the dependent variable. The PET, PRE, TMN, and TMX datasets were acquired from the Climate Research Unit Time-Series 3.24.01 (CRU TS 3.24.01). These data were derived from monthly observations from over 4000 meteorological stations distributed across the world's land areas. The gridded CRU TS 3.24.01 product is freely available for the science community on http://badc.nerc.ac.uk/data/cru or http://www.cru.uea.ac.uk. The reader is referred to [26] for more details on the construction of the CRU TS 3.24.01 product. The SM data was acquired from the European Space Agency (ESA), as part of their Climate Change Initiative (CCI) program. This product is a combination of both active and passive microwave sensors. It has a spatial resolution of 0.25 degrees, given in volumetric units (m^3 m^{-3}) and is provided in NetCDF-4 format. Maize production data sets per province in tons (tons), as well as the land area cultivated in hectares (ha) for maize production for the major maize-producing provinces were obtained from the abstract of agricultural statistics compiled by the Department of Agriculture, Forestry and Fisheries of South Africa (DAFF). This abstract document contains important information on inter alia, field crops, horticulture, livestock, vital indicators, total land area in hectares (ha) cultivated for maize production, and the contribution of primary agriculture to the South African economy. The data are available on the department's website (www.daff.gov.za). All datasets are extracted monthly and are averaged from October to April (average maize growing period in South Africa). This was done to ensure the same data scale as the maize data which was collected yearly. All datasets span from 1990–2017. Summary of the input data is given in Table 1.

Table 6-1: Summary of input data used for this study

Data Names	Abbreviation	Sources
Normalized Difference Vegetation Index	NDVI	MODIS (MOD13Q1)
Potential Evapotranspiration	PET	Climate Research Unit
Precipitation	PRE	Climate Research Unit
Minimum Temperature	TMN	Climate Research Unit
Maximum Temperature	TMX	Climate Research Unit
Soil Moisture	SM	European Space Agency
Size of land cultivated for maize production	Land	Department of Agriculture, Forestry and Fisheries

6.1.3. Data Analysis

6.1.3.1. Artificial Neural Network

In this study, the input variables include the PET, PRE, TMN, TMX, SM, and land cultivated for maize production. The mathematical model is presented in equation 1, where; y is the output, x_1, x_2 ……. x_n represents the input variables, w_1, w_2 ……. w_n represents the weights of the combination which generates the output, $\theta(.)$ is the unit step function, w_i are the weights related with the ith input and μ is the mean.

$$y = \theta \sum_{j=1}^{n} w_i \; x_i - \mu \tag{1}$$

The generalized weight w_i is defined as the contribution of the ith covariate to the log-odds, and was introduced by [27]. The equation below represents the generalized weight:

$$w_i = \frac{\partial \log\left(\frac{o(x)}{1 - o(x)}\right)}{\partial x_i} \tag{2}$$

where the generalized weight shows the effect of the individual covariate x_i and consequently has an analogous interpretation as the ith regression parameter in regression models, $o(x)$ is the predicted outcome probability by covariate vector and log-odds is the link function for the logistic regression model. Note that, the generalized weight depends on all other covariates.

The analysis was performed using the neuralnet package in R software. The neuralnet uses the supervised learning algorithms which comprise a flexible function that trains multilayer perceptron to a particular data set [28]. A two layer back propagation network with sufficient hidden nodes that has been proven to be a universal approximator was adopted [22,27]. The data were scaled in order to nullify the ambiguous effect that a variable might have on the prediction variable due to its scale. Hence, the min-max normalization was used to transform the data into a common range, thereby removing the scaling effect from all the variables. Both the dependent variable (maize) and independent variables were partitioned into training and test datasets. The training data consist of the 80% of the data (1990 to 2011) while the test data is 20% of the data (2012 to 2017). The training data is the set of data from which the system learns from and testing data is used to validate the model's performance by comparing the predicted maize yield with the actual maize yield. In order to improve the performance of the neural network different combinations of the input variables (PET, PRE, TMN, TMX, SM, and Land) with a vector (hidden neuron); (indicating the number of hidden layers and hidden neurons in each layer) were used with an automated loop to change the vector (architecture) for each province. Hence, the best combination of variables and architecture for each province was selected using the percentage of accuracy. The best combination for each province was then used to predict maize production and was compared with the testing data (20%) left out from the machine learning process. The projection was made using the avNNet function in Caret package in R. The performance measures of the prediction were accessed using the adjusted R^2. The projection for maize production for the years 2018 and 2019 was then performed.

6.2. Results

6.2.1. Optimizing Combinations of Variable Selection

Owing to the fact that there is no standard method for the selection of variables in the neuron network, it is usually done by testing various variable combinations so as to arrive at the best combination for the model. In this case, as reported by [29], the major agro-climatic variable that influences maize yield varies across the maize producing areas of South Africa. According to the current study, the TMX is the major determinant in the FS and MP provinces, while the TMN is largely responsible for changes in maize yield in the NW province. Both the PET and TMN are found to be the major drivers of maize yield in KZN. These variables were selected as a baseline for the variable combination check, by holding them constant in all the combinations. Since six variables (i.e., PET, PRE, TMN, TMX, Land and SM) were used in the model, 12 combinations were created for each province except for KZN province, which had just 10 because two climatic variables largely determine its maize yield. Table 2 illustrate the combination of variables, the hidden neuron, overall error, and accuracy of the best three ranked combinations that best predict maize yield in each of the provinces.

Table 6-2: Top five architecture of hidden configurations from different variable combinations; with scores, rank and the root mean squared error (RMSE) (Scores refers to the accuracy level (%) of the combination with the hidden neuron and ranked 1 to 5 accordingly)

Province	Combination of Variables	Hidden Neuron	Scores	Rank	RMSE
FS	TMX, Land, SM	8,9	76.64%	1	0.0383
		5,9	76.55%	2	0.0397
		5,7	76.28%	3	0.0381
		3,6	76.18%	4	0.0382
		7,8	76.13%	5	0.0393
	PET, PRE, TMN, TMX, Land, SM	5,8	82.42%	1	0.0374
		6,7	82.41%	2	0.0472
		4,9	82.02%	3	0.0445
		6,8	82.01%	4	0.041
		3,8	81.43%	5	0.0399
	PRE, TMN, TMX, Land, SM	2,6	82.46%	1	0.0347
		4,9	81.94%	2	0.0456
		4,5	80.80%	3	0.0457
		6,7	80.79%	4	0.0429
		8,9	79.19%	5	0.0483
NW	PRE,SM, TMN	5,6	71.51%	1	0.014
		3,5	71.26%	2	0.0166
		5,6	70.16%	3	0.0202
		6,9	69.99%	4	0.0152
		7,9	69.10%	5	0.0158
	TMN, Land, SM	3,4	73.74%	1	0.015
		2,5	72.33%	2	0.0179
		7,9	67.82%	3	0.0178
		3,6	67.77%	4	0.0172
		1,9	67.59%	5	0.0176
	TMN, SM	2,8	69.22%	1	0.0142
		4,9	69.06%	2	0.0147
		8,9	67.52%	3	0.0152
		3,8	67.08%	4	0.0170
		3,5	67.99%	5	0.0161
MP	TMN, TMX, Land, SM	3,4	93.79%	1	0.024
		3,5	91.02%	2	0.0267
		2,7	90.77%	3	0.0267
		6,9	90.73%	4	0.0271
		3,8	90.61%	5	0.0275

	PET, PRE, TMN, TMX, Land	7,9	92.02%	1	0.0243
		2,6	91.08%	2	0.0267
		4,9	90.64%	3	0.0273
		1,8	90.35%	4	0.0283
		1,4	89.99%	5	0.0262
	PET, TMX	4,7	88.39%	1	0.0246
		2,7	88.16%	2	0.0247
		8,9	87.77%	3	0.0248
		1,8	87.53%	4	0.0250
		3,8	87.51%	5	0.0245
KZN	PET, PRE, TMN, TMX	3,5	89.90%	1	0.0055
		4,6	89.66%	2	0.0055
		3,6	89.05%	3	0.0055
		3,9	88.95%	4	0.0055
		3,4	88.93%	5	0.0057
	PET, TMN, TMX, Land, SM	1,8	61.23%	1	0.0036
		1,9	61.20%	2	0.0036
		1,3	60.94%	3	0.0036
		3,5	47.19%	4	0.0036
		4,7	45.59%	5	0.0036
	PET, PRE, TMN, TMX, Land, SM	7,8	93.90%	1	0.0033
		4,7	92.15%	2	0.0037
		5,8	91.47%	3	0.0052
		4,5	90.64%	4	0.0055
		2,9	90.18%	5	0.0060

According to Table 2, in the FS province, the combination of TMX, Land and SM variables at different automated two hidden neurons with vector (8,9) ranked first within this group with 76.64% accuracy and has a root mean squared error (RMSE) of 0.038. The combination of the PET, PRE, TMN, TMX, Land and SM using vector (5,8) resulted in an accuracy of 82.42% and RMSE of 0.037 and ranked first. On the other hand, an accuracy of 82.46% and RMSE of 0.035 was achieved when PRE, TMN, TMX, Land and SM were combined using vector (2,6). Hence, the combination of variables PRE, TMN, TMX, Land and SM with vector (2,6) was chosen to model maize production for the FS province. For the NW province, the combination of only two variables TMN and SM using vector (2,8) gave an accuracy of 69.22% and had RMSE of 0.014. When PRE was added to TMN and SM but with vector (5,6) the accuracy improved to 71.51% with RMSE of 0.014. However, a higher accuracy of 73.74% with RMSE of 0.015 was attained with the variable combination of TMN, Land, and SM with vector (3,4). Considering the combination with the highest accuracy, a variable combination of TMN, Land and SM with vector (3,4) was selected for the model for the NW province.

Furthermore, for MP province, the combination of variables PET and TMX using vector (4,7) gave an accuracy of 88.39% and RMSE of 0.025. The accuracy for a variable combination that better combined to predict maize yield improved to 92.02% when PET, PRE, TMN, TMX and Land were combined. The accuracy further improved to 93.79% with RMSE of 0.024 when variables TMN, TMX, Land and SM were combined using vector (3,4). Consequently, the combination of TMN, TMX, Land and SM with vector (3,4) were selected as the model for MP province. In the case of KZN, the combination of PET, TMN, TMX, Land, and SM with vector (1,8) produced an accuracy of 61.23% and RMSE of 0.0036. When the PET, PRE, TMN and TMX were combined with vector (3,5) an accuracy of 89.39% was achieved. However, the combination of PET, PRE, TMN, TMX, Land, and SM using vector (7,8) gave 93.90% accuracy and RMSE of 0.003 in predicting maize yield in KZN. Therefore, the combination of the PET, PRE, TMN, TMX, Land and SM variables with two hidden neurons of (7,8) was selected for the model for KZN province.

6.2.2. Generalized Weight of the Variables ($\mathbf{w_i}$)

Tables 3–6 show the generalized weight expressing the effect of each independent variable on the dependent variable in the combination. As shown in Table 3, PRE, TMX and Land have a positive linear effect on maize production for all the trained years in the FS province. This indicates a favorable relationship between PRE, TMX, Land and maize production in the area with variance ranging from 0.01 to 0.42, 0.24 to 7.88 and 0.19 to 5.24 for PRE, TMX and Land, respectively. A negative effect is noticed between SM and maize production with variance ranging from –5.56 to –0.20, suggesting an unfavorable relationship between the two variables. Similarly, there exist both negative (40.91%) and positive (59.09%) effects between TMN and maize production for the trained year. The relationship was negative for years 1991, 1992, 1995, 2003, 2004, 2005, 2009, 2010, and 2011 with its variance ranging from –5.56 to –0.20, suggesting an unfavorable relationship between the two variables in those corresponding years.

Table 6-3: Generalized weight for the independent variable in Free State

Year	PRE	TMX	TMN	Land	SM
1990	0.09	1.18	0.03	1.02	–0.99
1991	0.09	0.88	–0.10	0.97	–0.88
1992	0.04	0.35	–0.07	0.45	–0.40
1993	0.01	0.28	0.04	0.19	–0.20
1994	0.42	7.88	1.05	5.24	–5.56
1995	0.05	0.52	–0.05	0.56	–0.52
1996	0.02	1.87	0.61	0.58	–0.86
1997	0.06	2.44	0.65	1.04	–1.32
1998	0.05	0.75	0.03	0.62	–0.61
1999	0.02	0.24	0.01	0.20	–0.20
2000	0.12	1.53	0.01	1.37	–1.32
2001	0.05	0.73	0.06	0.55	–0.56
2002	0.07	1.37	0.18	0.91	–0.96
2003	0.13	1.16	–0.14	1.32	–1.20
2004	0.13	1.10	–0.20	1.37	–1.22
2005	0.22	1.62	–0.39	2.18	-1.90
2006	0.17	2.16	0.03	1.91	–1.86
2007	0.04	0.59	0.04	0.47	–0.47
2008	0.08	1.27	0.10	0.96	–0.98
2009	0.04	0.37	–0.05	0.42	–0.38
2010	0.13	1.20	–0.14	1.35	–1.23
2011	0.07	0.76	–0.02	0.72	–0.69

The generalized weight for the independent variables for the NW province is shown in Table 4. Both TMN and Land depict a positive linear effect on maize production in the province with variance ranging from 1.12 to 1.70 and 0.36 to 0.54, respectively. This suggests a favorable relationship between the two independent variables and maize production in the province. On the other hand, SM has a negative linear effect on maize production in the province with the variance ranging from -1.55 to -0.95. This implies an unfavorable relationship between the two variables.

Table 6-4: Generalized weight for the independent variable in North West

Year	TMN	Land	SM
1990	1.12	0.37	–0.95
1991	1.41	0.38	–1.29
1992	1.52	0.39	–1.51
1993	1.70	0.43	–1.52
1994	1.43	0.39	–1.34
1995	1.62	0.48	–1.55
1996	1.66	0.42	–1.41
1997	1.58	0.42	–1.38
1998	1.59	0.43	–1.47
1999	1.66	0.49	–1.35
2000	1.59	0.49	–1.42
2001	1.53	0.54	–1.43
2002	1.36	0.36	–1.33
2003	1.39	0.36	–1.36
2004	1.41	0.37	–1.38
2005	1.44	0.40	–1.34
2006	1.47	0.41	–1.38
2007	1.44	0.39	–1.38
2008	1.26	0.39	–1.12
2009	1.47	0.40	–1.42
2010	1.41	0.40	–1.29
2011	1.50	0.42	–1.40

Table 5 depicts the generalized weight for the independent variables in MP province. The TMX depicts a positive linear effect on maize production in the province with its variance ranging from 1.19 to 2.23. This implies that TMX has a favorable relationship with maize production. However, TMN, Land and SM display a negative linear effect on maize production with their variance ranging from –1.03 to –0.25, –0.20 to –0.01 and –54 to –0.38, respectively. Thus, these variables have an unfavorable relationship with maize production in the province.

Table 6-5: Generalized weight for the independent variable in Mpumalanga

Year	TMX	TMN	Land	SM
1990	1.62	–0.44	–0.08	–0.45
1991	1.67	–0.45	–0.08	–0.47
1992	1.19	–0.25	–0.03	–0.40
1993	1.73	–0.61	–0.11	–0.47
1994	2.01	–0.76	–0.14	–0.51
1995	1.71	–0.51	–0.09	–0.47
1996	2.23	–0.92	–0.18	–0.54
1997	1.98	–0.73	–0.14	–0.51
1998	1.81	–0.56	–0.10	–0.50
1999	2.11	–0.78	–0.15	–0.53
2000	2.14	–1.03	–0.20	–0.50
2001	1.70	–0.79	–0.15	–0.41
2002	1.76	–0.59	–0.11	–0.47
2003	1.29	–0.16	–0.01	–0.43
2004	1.75	–0.52	–0.09	–0.49
2005	1.55	–0.41	–0.07	–0.46

2006	1.97	–0.69	–0.12	–0.51
2007	1.32	–0.26	–0.03	–0.43
2008	1.51	–0.49	–0.09	–0.41
2009	1.66	–0.44	–0.08	–0.48
2010	1.58	–0.38	–0.06	–0.46
2011	1.34	–0.50	–0.08	–0.38

As depicted in Table 6, the PET and SM have a negative linear effect on maize production in KZN province with their variance ranging from –6.22 to –1.04 and –5.37 to –1.61, respectively. Therefore, these variables have an unfavorable relationship with maize production in the area. The following variables PRE, TMX, and Land display a positive linear effect on maize production in the province and their variances range from 0.42 to 1.06, 1.95 to 8.76 and 0.76 to 2.95, respectively. The case is different for TMN where 45.45% of this variable has a negative linear effect on maize production in the area as its variance ranges from –1.66 to –0.02. The remaining 54.55% has a positive linear effect on maize production in the province and its variance ranges from 0.13 to approximately 1.81.

Table 6-6: Generalized weight for the independent variable in KwaZulu-Natal

Year	**PET**	**PRE**	**TMX**	**TMN**	**Land**	**SM**
1990	–1.69	0.63	2.93	–1.66	1.00	–2.97
1991	–5.33	0.92	8.76	–0.56	2.95	–5.37
1992	–1.78	0.59	3.00	0.31	1.31	–2.05
1993	–1.17	0.55	2.08	0.18	0.95	–1.66
1994	–5.02	1.06	8.00	0.91	2.92	–4.88
1995	–2.69	0.64	4.57	–0.83	1.57	–3.26
1996	–1.74	0.69	3.28	–0.29	1.35	–2.40
1997	–2.28	0.71	4.01	0.26	1.58	–2.60
1998	–2.03	0.69	3.60	0.37	1.49	–2.33
1999	–3.18	0.76	5.06	0.54	1.99	–3.24
2000	–6.22	0.59	8.49	1.81	2.41	–5.09
2001	–3.80	0.68	5.82	1.00	1.90	–3.53
2002	–1.33	0.50	2.28	–0.02	0.93	–1.81
2003	–1.43	0.54	2.42	–0.09	0.99	–1.97
2004	–1.25	0.55	2.13	–0.93	0.79	–2.26
2005	–1.54	0.64	2.78	–0.07	1.22	–2.12
2006	–1.63	0.59	2.90	0.28	1.22	–1.96
2007	–1.33	0.42	2.01	0.26	0.76	–1.67
2008	–1.47	0.55	2.48	–0.98	0.89	–2.43
2009	–1.04	0.59	1.95	–0.32	0.87	–1.87
2010	–1.21	0.62	2.33	0.13	1.14	–1.72
2011	–1.35	0.51	2.43	0.20	1.13	–1.61

6.2.3. Network Topology

The training process results are illustrated in Figure 2A–D. The figure reflects the structure of the trained neural network for each province. The network topology conveys basic information such as the trained synaptic weights, the number of steps needed for converge and the overall errors. For the purpose of this study, the threshold for the partial derivatives of the error function was set at 0.01. Each province has its own unique variable combinations as well as hidden neurons (see Table 2; i.e., the FS province has PRE, TMN, TMX Land and SM with hidden neuron c(2,6); NW province TMN, Land and SM with hidden neuron c(3,4); MP province TMN, TMX, Land, and SM with hidden neuron c(3,4); and KZN province PET, PRE, TMN, TMX, Land and SM with hidden neuron c(7,8).

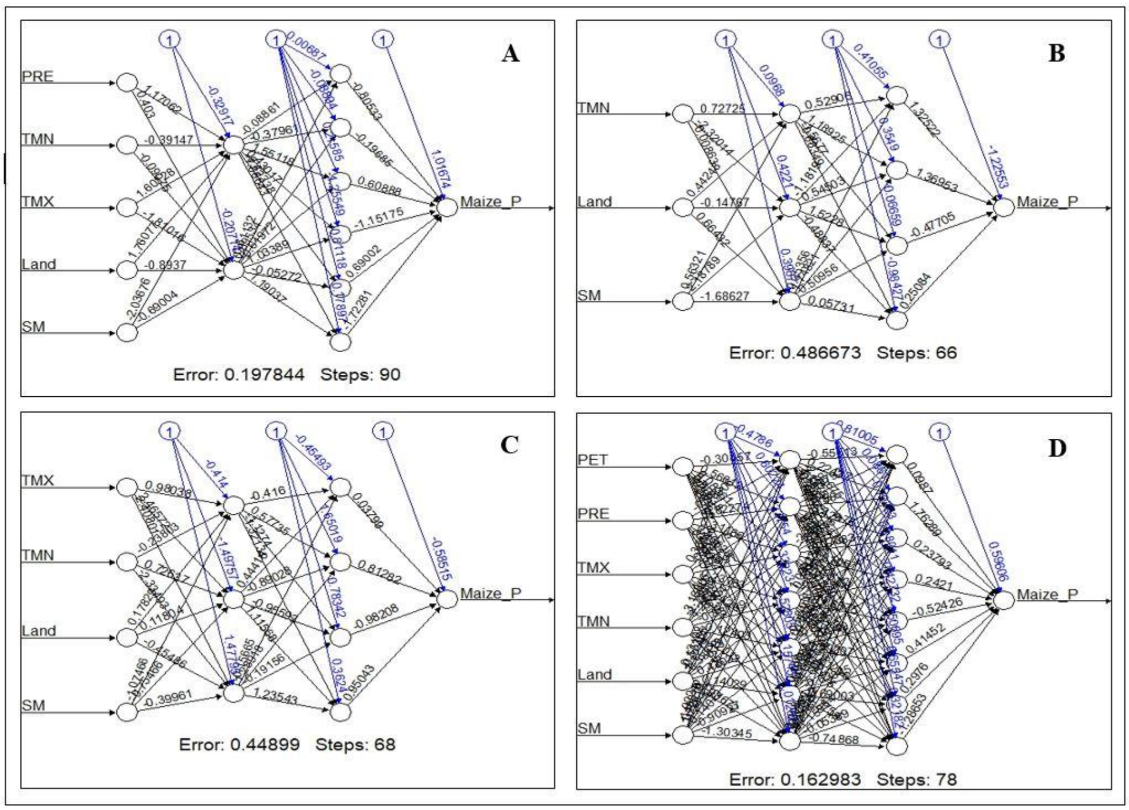

*Figure 6-2: Neural network topology for the best combined variables for (**A**) FS: Free State, (**B**) NW: North West, (**C**) MP: Mpumalanga and (**D**) KZN: KwaZulu-Natal provinces*

Figure 2A shows that in the FS province, the training process needed 90 steps to achieve less error function (i.e., < threshold of 0.01). The process has an overall error of about 0.20. In the NW province, according to Figure 2B, the training process needed 66 steps until all absolute partial derivative of the error function were smaller than 0.01 with the process having an overall error of about 0.49. On the other hand, in MP province (Figure 2C), the training process needed 68 steps until all absolute partial derivatives of the error function were smaller than the default threshold of 0.01 with the process having an overall error of about 0.45. In KZN (see Figure 2D) the training process needed 78 steps until all absolute partial derivatives of the error function were smaller than 0.01, and the overall error was 0.16.

6.2.4. Maize Prediction and Validation

Having trained the neural network with 80% of both the independent and dependent variables, and the best combinations with the hidden neuron selected, the prediction for maize production per province was made for the same time frame (2012–2017) of the testing data (20%). The predicted output was then compared with the reserved 20% that was not used for machine learning. The results are displayed in Tables 7–10. The accuracy level of the prediction varies for each province. For instance, the model for the FS province has an adjusted R^2 of 0.75, and NW, MP and KZN provinces have an R^2 of 0.67, 0.86 and 0.82, respectively.

Table 6-7: Comparison between predicted and actual maize production for Free State ("000 tons)

Year	Actual Maize Production	Predicted Maize Production	Difference (Predicted-Actual)	Deviation
2012	4884.8	4254.24	–630.56	–0.13
2013	6247.25	4146.92	–2100.33	–0.34
2014	3945	3939.01	–5.99	–0.002
2015	2213.5	2789.29	575.79	0.26
2016	7330.5	3961.63	–3368.87	–0.46
2017	5515.9	3844.02	–1671.88	–0.30

As depicted in Table 7, the predicted maize production in the FS province deviated from the actual maize production by –0.13 (13%), –0.34 (34%), –0.002 (0.2%), –0.46 (46%) and –0.30 (30%) for years 2012, 2013, 2014, 2016, and 2017, respectively. The results suggest an under-prediction of maize production in the province. On the other hand, 2015 resulted in over-prediction (i.e., 0.26 which is equivalent to 26%) of maize production.

Table 6-8: Comparison between predicted and actual maize production for North West ("000 tons)

Year	Actual Maize Production	Predicted Maize Production	Difference (Predicted-Actual)	Deviation
2012	1613	1671.57	58.57	0.04
2013	2898	1956.05	-941.95	-0.33
2014	1490	1830.38	340.38	0.23
2015	1141	1416.96	275.96	0.24
2016	3135	1934.21	-1200.79	-0.38
2017	2123.5	1841.02	-282.48	-0.13

As shown in Table 8, the predicted maize production for the NW province deviated from the actual maize production by –0.33 (33%), –0.38 (38%), and –0.13 (13%) for 2013, 2016 and 2017 respectively, thus there was under-prediction of maize production. Contrasting this, maize production was over-predicted by 0.04 (4%), 0.23 (23%) and 0.24 (24%) in 2012, 2014 and 2015, respectively.

Table 6-9: Comparison between predicted and actual maize production for Mpumalanga ("000" tons)

Year	Actual Maize Production	Predicted Maize Production	Difference (Predicted-Actual)	Deviation
2012	3005	2721.47	–283.53	–0.09
2013	2782.2	2552.24	–229.96	–0.08
2014	2429.3	2192.19	–237.11	–0.10
2015	2319	2308.74	–10.26	–0.004
2016	3431	2761.67	–669.33	–0.20
2017	2880	2670.98	–209.02	–0.07

From Table 9, maize production is under-predicted for the MP province across the entire testing period by –0.09 (9%), –0.08 (12%), –0.10 (10%), –0.004 (0.4%), –0.20 (20%) and –0.07 (7%) for the years 2012, 2013, 2014, 2015, 2016, and 2017, respectively.

Table 6-10: Comparison between predicted and actual maize production for KwaZulu-Natal ("000 tons)

Year	Actual Maize Production	Predicted Maize Production	Difference (Predicted-Actual)	Deviation
2012	599	520.82	–78.18	–0.13
2013	559.1	541.99	–17.11	–0.03
2014	507.5	476.63	–30.87	–0.06
2015	522	468.26	–53.74	–0.10
2016	735	572.21	–162.79	–0.22
2017	682.5	615.61	–66.89	–0.10

In KZN province according to the results presented in Table 10, maize production was under-predicted by –0.13 (13%), –0.03 (3%), –0.06 (6%), –0.10 (10%), –0.22 (22%) and –0.10 (10%) in 2012, 2013, 2014, 2015, 2016 and 2017, respectively.

6.2.5. Maize Production Projection

The results of the projected maize production performed with AvNNet() in Caret package across each province for the year 2018 and 2019 is shown in Figure 3A–D and Table 11. The results indicate that maize production will decrease across all the provinces (except FS) from the current year 2017 to 2018 and 2019. The FS depicts a 32% increase in maize production, i.e. from 2018 (4651.03 tons) to 2019 (6146.33 tons). In Figure 3A–D, the dark gray shaded and light gray shaded area is the 80% and 95% prediction confidence interval, respectively.

Table 6-11: Projected maize production for FS: Free State, NW: North West, MP: Mpumalanga and KZN: KwaZulu-Natal for 2018 and 2019 using the best variable combinations for each province ("000 tons)

Year	FS	NW	MP	KZN
2018	4651.03	2403.94	2604.34	602.73
2019	6146.33	2361.61	2335.61	572.74
Difference	1495.3	–42.33	–268.73	–29.99
Deviation	0.32	–0.02	–0.10	–0.05

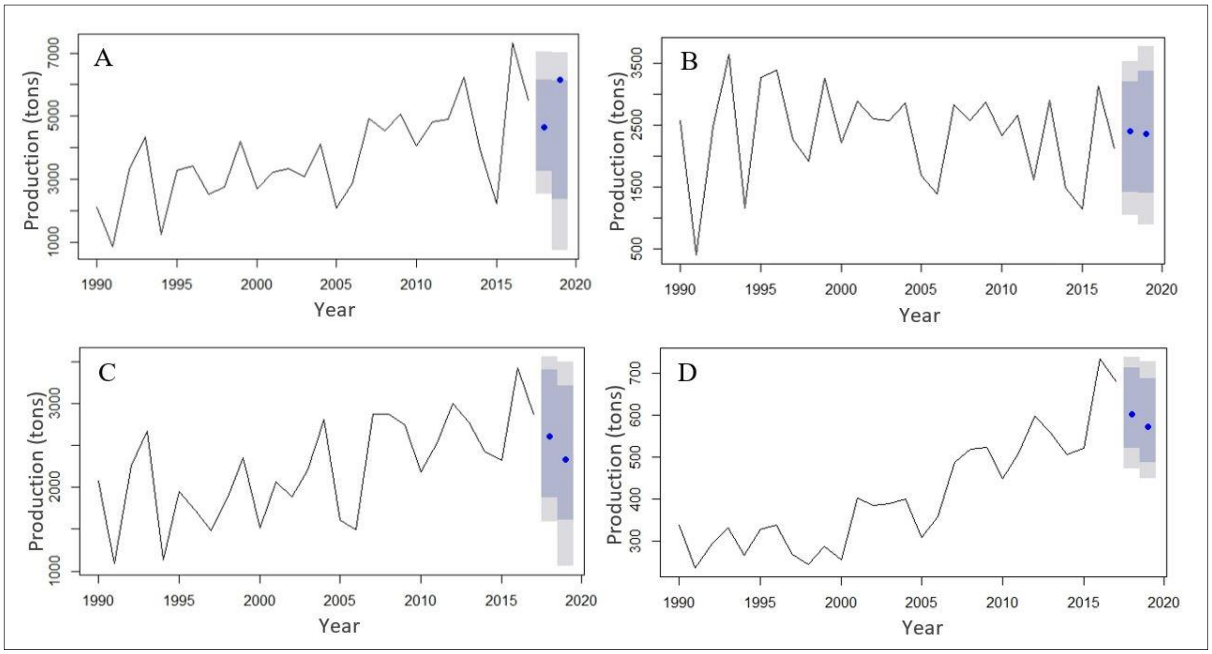

*Figure 6-3: Projected maize production (tons) for (**A**) FS: Free State, (**B**) NW: North West, (**C**) MP: Mpumalanga and (**D**) KZN: KwaZulu-Natal provinces; with 80% confidence interval in dark grey and 95% confidence interval in light grey*

6.3. Discussion

In this study, maize production in the FS, NW, MP and KZN provinces of South Africa was modeled based on the ANN approach. The analysis considered various variable combinations and ranked the accuracy of these combinations across the study area. The results indicated spatial dependence of different combinations in different provinces. For instance, the PRE, TMN, TMX, Land and SM with hidden neuron c(2,6) combination were ranked first in the FS province; TMN, Land and SM with hidden neuron c(3,4) in the NW province; TMN, TMX, Land, and SM with hidden neuron c(3,4) in MP and lastly, PET, PRE, TMN, TMX, Land and SM with hidden neuron c(7,8) ranked first in KZN. The three variables, i.e. TMN, Land and SM, seem to dominate in all first ranked levels across all the four provinces.

Maize production in the four selected provinces is highly affected by different agro-climatic parameters, as reported in [29]. In this study, we found that TMX is the main driver of change in maize yield in the FS and MP, whereas TMN has a dominant impact in the NW. The PET and TMN climate variables dominate in KZN, hence significantly affecting the maize yield in the province. The results indicate that the variables have a linear effect on maize production since their variance was very small. In addition, the influence of TMN on maize production varied in the NW, FS and KZN, having a positive linear effect. However, the TMN in MP exhibited a negative linear effect on maize production. The land has a positive linear effect on maize production across all the provinces except for MP where it has a negative linear effect. Similarly, SM exhibited a negative linear effect on maize production across all the provinces. The TMX displayed a positive linear effect on maize production in the FS, MP and KZN. PRE appeared in the variable combination of just two provinces (FS and KZN) and it has a positive linear effect on maize production in both of these provinces.

The accuracy of the combined variables to predict maize production varied across the provinces. The accuracy was recorded in MP (93.79%) and KZN (93.90%). This accuracy suggests that the TMN, TMX, Land and SM are sufficient for modelling maize production in MP province while PET, PRE, TMN, TMX, Land and SM are ideal for the effective modelling of maize production in KZN. Nevertheless, these results do not extensively mean that other farm management practices such as fertilizer application, irrigation and choice of cultivar are not significant in achieving best output for maize production. They are thought to account for the deviations in the comparison between the actual and predicted maize production. On the other hand, despite the high accuracy of about 82.46% of the combined variables of PRE, TMN, TMX, Land and SM to predict maize production in the FS, a high deviation is noticed between the actual maize production and predicted production particularly in the year 2016 where maize is up by 46%. These results are in contrast with the deviation between actual and predicted maize production in the NW where the selected combination of TMN, Land and SM gave an accuracy of 73.74% but gave a smaller deviation between actual and predicted maize production. This could suggest that the FS province is more prone to the influence of other farm management practices.

The projected maize production indicates that maize production is on the decline across all the provinces. This can be attributed to the future trend of changes in climatic variables as well as a projected increase in drought occurrences [29,30].

6.4. Conclusions

This study demonstrates the value of the artificial neural network in predicting maize yield across the four major maize producing provinces of South Africa. These results agree with the previous research findings [27]. The results indicate that different climatic variables and/or their combinations serve(s) as major drivers for maize production across the different provinces. The accuracy level of the prediction obtained between the actual and predicted maize production for each province as given by the adjusted R^2 value, with 0.75 in the FS, 0.67 in the NW, 0.86 in MP and 0.82 in KZN. In this study, the adjusted R^2 is used as a measure of future prediction of maize production.

Although the predicted maize production is under-predicted, we conclude that it is better to under-predict than over-predict. This is because an under-prediction will enhance the decision-making process of the farmers and/or the policymakers to put in place measures to ensure that loss of production is prevented or minimized, rather than be blinded by expectation of high production. In addition, all the predictions (under-predictions), particularly in MP and KZN, are within 10% of the actual maize production except for the year 2016, in which the production was approximately 20%.

The decline in projected maize production can be attributed to the effects of climate change and variability; hence adequate adaptation and coping measures are needed for both commercial and small-scale farmers to prevent loss of production and aggravated famine.

This research study is essential in South Africa, as food security is threatened by drought due to climate change and variability. The availability of historical and current agro-climatic data combined in a model could serve as a vital decision support system to cope and mitigate climate change. The model is developed to incorporate different farming scenarios such as the combination of agro-climatic parameters with different farming practices to predict maize yield. Hence, this tool can help farmers to make informed choices, which include mitigation and adaptation measures in order to maximize profit on crop production. Furthermore, the model will be operationalized and made available to relevant stakeholders and decision makers such as commercial and small-scale farmers and the Department of Agriculture.

This study can be improved to ensure its operability by incorporating other farm management practices such as fertilizer application that was not available/accessible during the period of undertaking this research. However, the current status of this model can be validated by comparing the projected production of maize with the actual production at the end of the 2018 and 2019 season.

Author Contributions: The conceptualization, methodology, formal analysis and writing—original draft preparation by O.M., Supervision, review and editing by J.B., A.H. and E.T. Data curation, formal analysis, writing—review and editing by A.A. and C.B.

Funding: This research received no external funding.

Acknowledgments: The authors gratefully acknowledge the financial support from the Department of Library Services and Department of Geography, Geoinformatics and Meteorology, University of Pretoria. The authors are also grateful to the reviewers for constructive comments and suggestions that assisted in improving the quality of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. World Wildlife Fund. *Meeting Report and Recommendations. From the Sustainable Food for the 21st Century Advisory Panel*; World Wildlife Fund: Washington, DC, USA, 2018.

2. Lobell, D.B.; Field, C.B. Global scale climate crop yield relationships and the impacts of recent warming. *Environ. Res. Lett.* **2007**, *2*, 014002, doi:10.1088/1748-9326/2/1/0140.

3. Fortin, J.G.; Anctil, F.; Parent, L.E; Bolinder, M.A. Site-specific early season potato yield forecast by neural network in Eastern Canada. *Precis. Agric.* **2011**, *12*, 905–923.

4. Alvarez, R. Predicting average regional yield and production of wheat in the Argentine Pampas by an artificial neural network approach. *Eur. J. Agron*. **2009**, *30*, 70–77.

5. Yang, C.; Peterson, C.L.; Shropshire, G.J.; Otawa, T. Spatial variability of field topography and wheat yield in the Paleous region of the Pacific Northwest. *Trans. ASAE* **1998**, *41*, 17–27.

6. Ghodsi, R.; Yani, R.M.; Jalali, R.; Ruzbahman, M. Predicting wheat production in Iran using an artificial neural networks approach. *IJARBSS* **2012**, *2*, 34–47.

7. Paswan, R.P.; Begum, S.A. Regression and neural networks models for prediction of crop production. *IJSER* **2013**, *4*, 2229–5518.

8. Dalgliesh, N.; Saifuzzaman, M.; Khan, I.; Hossain, A.B.S.; Rawson, H. *Expanding the Area for Rabi-season Cropping in Southern Bangladesh*; Final Report LWR/2005/146; Australian Centre for International Agricultural Research (ACIAR): Canberra, Australia, 2012.

9. Gonzalez-Sanchez, A.; Frausto-Solis, J.; Ojeda-Bustamante, W. Attribute selection impact on linear and nonlinear regression models for crop yield prediction. *Sci. World J.* **2014**, *2014*, 509249.

10. Abdipour, M.; Younessi-Hmazekhanlu, M.; Ramazani, S.H.R.; Omidi, A.H. Artificial neural networks and multiple linear regression as potential methods for modeling seed yield of safflower (Carthamus tinctorius L.). *Ind. Crops Prod.* **2019**, *127*, 185–194.

11. Klemme, R.M. An econometric yield response and forecasting model for corn in Indiana. Master's Thesis, Purdue University, West Lafayette, IN, USA, August 1978.

12. Molazem, D.; Valizadeh, M.; Zaefizadeh, M. North West of genetic diversity of wheat. *J. Agric. Sci*. **2002**, *20*, 353–365.

13. Zaefizadeh, M.; Khayatnezhad, M.; Gholamin, R. Comparison of multiple linear regressions and artificial neural network in predicting the yield using its components in the Hassle Barley. *American-Eurasian J. Agric. & Environ. Sci.* **2011**, *10*, 60–64.

14. O'Neal, M.R.; Engel, B.A.; Ess, D.R.; Frankenberger, J.R. Neural network prediction of maize yield using alternative data coding algorithms. *Biosyst. Eng.* **2002**, *83*, 31–46.

15. Caselli, M.; Trizio, L.; de Gennaro, G.; Ielpo, P. A simple feedforward neural network for the PM10 forecasting: comparison with a radial basis function network and a multivariate linear regression model. *Water Air Soil Pollut*. **2009**, *201*, 365–377.

16. Liu, J.; Goering, C.E. Neural network for setting target corn yields. Presented at the ASAE Annual International Meeting, 18–21 July 1999, St. Joseph, MI, USA, 1999; Paper No. 993040.

17. Liu, J.; Goering, C.E.; Tian, L. A neural network for setting target corn yields. *Trans. ASAE*. **2001**, *44*, 705–713.

18. Hsieh, W.W. Machine learning methods in the environmental sciences: neural networks and kernels. Cambridge University Press. New York, NY, USA, 2009; pp. 349.

19. DAFF (Department of Agriculture, Forestry and Fishery). Trends in the Agricultural Sector. Available online: https://www.daff.gov.za/Daffweb3/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Trends%20in%20the%20Agricultural%20Sector%202017.pdf (accessed on 11 July 2018).

20. Food and Agriculture Organization of the United Nations (FAO). World food situation: FAO cereal supply and demand brief. http://www.fao.org/worldfoodsituation/csdb/en/ (accessed on 17 September 2018).

21. Kaul, M.; Hill, R.L.; Walthall, C. Artificial neural network for corn and soybean prediction. *Agr. Syst*. **2005**, *85*, 1–18.

22. Drummond, S.; Joshi, A.; Sudduth, K.A. Application of neural network: precision farming, In 1998 IEEE International Joint Conference on Neural Networks Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98CH36227), Anchorage, AK, USA, 4-9 May 1998; IEEE: Piscataway, NJ, USA, 1998.

23. Kross, A.; Znoj, E.; Callegari, D.; Kaur, G.; Sunohara, M.; van Vliet, L.; Rudy, H.; Lapen, D.; McNairn, H. Evaluation of an artificial neural network approach for prediction of corn and soybean yield. In Proceedings of the 14th International Conference on Precision Agriculture, 24-27 June 2018, Montreal, Canada; International Society of Precision Agriculture: Monticello, IL, USA, 2018.

24. Matsumura, K.; Gaitan, C.F.; Sugimoto, K.; Cannon, A.J. Maize yield forecasting by linear regression and artificial neural networks in Jilin, China. *J Agr Sci*. **2015**, *153*, 399–410

25. Schulze, R.E. On observation, climate challenges, the South African agriculture sector and considerations for an adaption handbook. In: Handbook for farmers, officials and other stakeholders on adaptation to climate change in agriculture sector within South Africa. Schulze, R.E., Ed.; Thematic booklet, Department: Agriculture, Forestry & Fisheries (DAFF): Pretoria, South Africa, 2016.

26. Harris, I.; Jones, P.D.; Osborn, T.J.; Lister, D.H. Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 Dataset. *Int. J. Climatol.* **2014**, *34*, 623–642.

27. Intrator, O.; Intrator, N. Interpreting neural-network results: a simulation study. *Comput. Stat. Data An.* **2001**, *37*, 373–393.

28. Frauke, G.; Stefan, F. neuralnet: Training of neural networks. *R J.* **2010**, *2*, 30–38.

29. Adisa, O.M.; Botai, C.M.; Botai, J.O.; Hassen, A.; Darkey, D.; Tesfamariam, E.; Adisa, A.F.; Adeola, A.M.; Ncongwane, K.P. Analysis of agro-climatic parameters and their influence on maize production in South Africa. *Theor. Appl. Climatol.* **2017**, *134*, 991–1004.

30. Adisa, O.M.; Botai, J.O.; Hassen, A.; Darkey, D.; Adeola, A.M.; Tesfamariam, E.; Botai, C.M.; Adisa, A.T. Variability of satellite derived phenological parameters across maize producing areas of South Africa. *Sustainability*. **2018**, *10*, 3033; doi:10.3390/su10093033.

Chapter 7

SUMMARY AND CONCLUSIONS

7.0. Summary of findings

The influence of climate change and variability on agriculture is well documented and is projected to have more negative impact in sub-Saharan Africa where there is poor coping and adaptive capacity. The projected impact is foreseen to further cause a strain on food security for the rapidly growing population. For this study, maize a major important grain crop in South Africa, being both the main feed grain and the staple food for most of the South African population was used. Maize is dominantly produced in four provinces of South Africa, accounting for about 84% of the country's total production. South Africa is classified as a semi-arid region and a particularly a-water stressed country. With the evidence of climate change and variability in the amount of rainfall received, many sectors such as agriculture and water face a direct impact of the consequences. To this end, many studies have been conducted towards ensuring sustainability in food production and water utilities.

This study through its literature review, found that climate change studies have been extensively conducted in South Africa, however, only a handful is related to maize production. Similarly, several studies on maize production have been performed using different methodologies but predominantly crop based models (see chapter 2: Literature review). Furthermore, it was found that many of the studies have relied on the use of climatic observation data which in most cases are inadequate due to poor spatial distribution of the stations, lengthy gaps in the data among others. In addition, the literature review found that, previous studies, have at best quantified the impact of climatic variables on maize and at a small geographic area. Attempts to predict maize yield have been minimal and the use of artificial intelligence such as the artificial neural network has not been conducted or reported in any publication. In this study, alternative sources of climatic and environmental data have been employed using remotely sensed data. Remote sensing defined as the acquisition of information from an object or phenomenon without physical contact with it offers possibilities of collecting continuous data over a large area (including remote areas) using satellite.

Considering the above, this study aimed to examine the variation in maize yield and develop a framework for predicting maize yield in response to climate change. To achieve this aim, this study has analyzed the impact of agro-climatic parameters on maize production across the major four maize producing provinces of South Africa. This study went further to investigate changes in the satellite derived phenological parameters and its relationship with maize production. In addition, the influence of drought (a derivative of climate change) on maize production was investigated. The study concluded by integrating all datasets used in each objective to develop an empirical predicting model using artificial neural network.

The analysis of four agro-climatic variables (precipitation, potential evapotranspiration, minimum and maximum temperatures) spanning a period of 1986–2015, over the North West, Free State, Mpumalanga and KwaZulu-Natal (KZN) provinces, indicated that there is a negative trend in precipitation for North West and Free State provinces and positive trend in maximum temperature for all the provinces over the study period. Further more, the result showed that one or more different agro-climatic variables influence maize more across the province. For example, minimum temperature had the most influence on maize production in North West, potential evapotranspiration (combination of the agro-climatic parameters), minimum and maximum temperature influenced maize production in KwaZulu-Natal while maximum temperature influenced maize production in Mpumalanga and Free State. In general, the agro-climatic parameters were found to contribute 7.79 %, 21.85 %, 32.52 % and 44.39 % to variation in maize production during the study period in North West, Free State, Mpumalanga and KwaZulu-Natal respectively. The variation in maize production amongst the provinces under investigation could most likely attributed to the variation in the size of the cultivated land among other factors including soil type and land tenure system. There were also difference in yield per hectare between the provinces; KwaZulu-Natal and Mpumalanga being in the humid subtropical areas of South Africa had the highest yield per hectare 5.61 tons and 4.99 tons respectively while Free State and North West which are in the semi-arid region had the lowest yield per hectare 3.86 tons and 3.03 tons respectively. Understanding the nature and interaction of the dominant agro-climatic parameters discussed in the present study as well as their impact on maize production will help farmers and agricultural policy makers to understand how climate change exerts its influence on maize production within the study area to better adapt to the major climate element that either increases or decreases maize production in their respective provinces (Chapter 3).

Furthermore, changes in phenological parameters of maize as well as their causal factors across the selected maize producing provinces were investigated. Climate change and variability are known to cause changes in crop phenology. The changes in phenology can be used as a proxy to elucidate the short- and long-term trends in climate change and variability. Climate change and or climate variability affects plant phenology largely during the vegetative and reproductive stages. Five phenological parameters i.e. the length of season (LOS), start of season (SOS), end of season (EOS), position of peak value (POP), and position of trough value (POT) derived from the MODIS NDVI data (MOD13Q1) were analysed. In addition, climatic variables (Potential Evapotranspiration (PET), Precipitation (PRE), Maximum (TMX) and Minimum (TMN) Temperatures spanning from 2000 to 2015 were also analysed. Based on the results, the maize producing provinces considered exhibit a decreasing trend in NDVI values. The results further show that Mpumalanga and Free State provinces have SOS and EOS in December and April respectively. In terms of the LOS, KwaZulu-Natal Province had the highest days (194) followed by Mpumalanga with 177 days while North West and Free State provinces had 149 and 148 days respectively. The results further demonstrate that the influences of climate variables on phenological parameters exhibit a strong space-time and common covariate dependence. For instance, TMN dominated in North West and Free State, PET and TMX are the main dominant factors in KwaZulu-Natal province whereas PRE highly dominated in Mpumalanga. Furthermore, the result of the Partial Least Square Path Modeling (PLS-PM) analysis indicates that climatic variables predict about 46% of the variability of phenology indicators and about 63% of the variability of yield indicators for the entire study area. The goodness of fit index indicates that the model has a prediction power of 75% over the entire study area. This study contributes towards enhancing the knowledge of the dynamics in the phenological parameters and the results can assist farmers to make the necessary adjustment in order to have an optimal production and thereby enhance food security for both human and livestock (Chapter 4).

In addition, the understanding of how climate extremes such as drought influences crop yield are critical in ensuring future global food security. Therefore, two commonly used drought indices; the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) were assessed to understand the impacts of drought on maize yield over four main maize production provinces of South Africa. The drought was characterized based on three Drought Monitoring Indicators (DMI) i.e., Drought Duration (DD), Drought Severity (DS), and Consecutive Drought Months (CDM). The results indicate that maize yield is significantly affected by drought across the entire study area, although the impacts are localized. A comparison between the two SPI and SPEI suggests that the SPEI is more correlated and more sensitive to maize yield than its counterpart. The yield is most sensitive to 3-month timescale coinciding with maize growing season ($r = 0.59$; $p < 0.05$). Based on the results, drought affects maize yield by up to 35% across the study area. This study illustrates the spatial patterns of drought showing locations with drought severity, frequency, and intensity which has the potential to influence crop yield. The result suggests that management strategies that allow for optimal water use within the first 1- and 3-month will be most effective for sustainable maize production within the study area. This study provides bases for the implementation of an early warning system that focuses on drought impact on crop yield (Chapter 5).

In ensuring and fulfilling one of the seventeen sustainable development goals; to *eradicate extreme poverty and hunger,* the development of a system capable of monitoring and predicting crop yield becomes imperative (FAO, 2016). The use of crop-based models are known to be expensive to implement and calibration intensive due to the fact that many of the models are developed to suite the climate of the origin. Machine learning tools such as the artificial neural network becomes handy and useful to providing a platform that is data intensive and robust to meet the requirements for an effective monitoring and predictive system for crop; particularly maize. This study developed an artificial neural network to predict maize in the major maize producing provinces of South Africa. Maize production prediction and projection was made using different mostly suitable combinations of climate variables that include precipitation (PRE), maximum temperature (TMX), minimum temperature (TMN), potential evapotranspiration (PET), soil moisture (SM) and land cultivated (Land) for maize. The result indicated that the variable combination of PET, PRE, TMN, TMX, Land, SM with two hidden neurons of vector (5,8) was the best combination to predict maize production in FS, the combination of TMN, TMX, PET, PRE, SM and Land with vector (7,8) resulted as the best combination for predicting maize in KZN while the combinations of TMN, SM and Land; TMN, TMX, SM and Land with vector (3,4) gave the best maize predicting combinations for NW and MP respectively. The comparison between the actual and predicted maize production using the testing data indicated performance accuracy adjusted R^2 of 0.75 for FS, 0.67 for NW, 0.86 for MP and 0.82 for KZN. Furthermore, the result suggested a decline in the projected maize production across the entire province from 2018 to 2019 except for FS with an increasing projection. The result is suggestive of the projected changes in climate and its derivatives such as drought. The developed model can help to enhance decision making process of the farmers and policymakers (Chapter 6).

In conclusion, this research contributes to this vital topic through investigating the most dominant climatic variables that influence maize yield in four provinces of South Africa. It is evident from this study that in the context of global change, increase in temperature leads to higher rate of evapotranspiration. On the other hand, decrease in precipitation leads to prolonged drought conditions which impact negatively on maize production. Furthermore, analysis of the phenological parameters for different types of vegetation in large areas helps to evaluate the impacts of climate change e.g., vulnerable ecosystems. At present, the phenology metrics that are derived from the time series of MODIS Normalized Difference Vegetation Index (NDVI) are recognized to provide an alternative methodology of crop condition monitoring compared to the expensive and time-consuming manual system. These phenological parameters have important applications such as in irrigation management, nutrient management, health management, yield prediction and crop type mapping vital for ensuring the security of the food crop production. Similarly, drought impacts on maize yield depend on drought magnitude and duration and on plant growth stages when droughts occur. Drought events during maize reproductive and vegetative stages cause the highest reduction in maize yield. The reduced maize yield during the notable drought years (1991/92, 1994/95, 2002/03, 2004/05, 2006/07, 2008/09, 2009/10, 2011/12 and 2014/15) could be attributed to the low rainfall amount during the growing season in some parts of NW. Persistent moderate drought conditions occurred during the sensitive growing stages of maize in some parts KZN and MP provinces. Consequently, farmers are always faced with the risk of losing their crops and eventually losing their income at every planting season. To reduce yield loss or failure, the following points can be considered;

- Farmers in Mpumalanga and KwaZulu-Natal could practise conservation agriculture whereby mechanical disturbance of soil is reduce and suitable variety of crops are grown.
- Farmers in humid-subtropical areas of KwaZulu-Natal and Mpumalanga should get involved more in maize production since these areas favour maize yield per hectare more compared to the semi-arid areas (that is Free and North West).
- Identification of suitable maize varieties that tolerate frost for North West and drought and heat wave for Free State can be of great help.

7.1. Scientific contribution of this study

All objectives of this research as well as the literature review are intended to be published in peer-reviewed journal hence the choice of the publication style of thesis writing. This will ensure that the scientific community particularly climate and agriculture research have access to recent findings and further contribute to knowledge. In addition, study such as this can be used as a tool to assess the vulnerability of agriculture/farms (particularly maize farms) to climate change which can help smallholder farmers to provide evidence to have access to insurance benefits and loans. Furthermore, reliable high-quality long-term remote sensing datasets, such as the MODIS NDVI dataset, are a crucial input for providing converging evidence on vegetation changes. While much is to be learned regarding the human dimension of adaptation, such evidence is highly needed to inform potential adaptation strategies for smallholder farmers in South Africa.

7.2. The potential contribution of this work to food security

With established evidence of climate change, reports have shown variations in climatic parameters as well as increase in the frequency and intensity of extreme climate events. These changes have potentials to affect crop production with more devastating impact on low coping capacity countries such as South Africa. The potential implication of this research is that by developing a crop monitoring and predicting model, adequate farm management practices can be selected. The empirical model developed in this research can also be adapted to other grain crops such as Sorghum, wheat, soya beans etc. The developed model will be made available to both small-scale and commercial farmers and the Department of Agriculture for adequate policy planning.

7.3. Limitations of the study

This study amidst of its good outputs is not free from limitations. A major limitation of this research is the lack of availability of maize data at higher scale i.e., at intra-season and at the farm level. If such data is available it could help to further establish the relationship between the agro-climatic, phenological parameters and maize production at seasonal and farm level. Also, worthy of mentioning is the inaccessibility to or lack of adequate farm management data such as fertilizer, irrigation data.

7.4. Future research direction

The developed model will be integrated into a climate change model to simulate future maize yield outlook using different climate change scenarios.

SUPPLEMENTARY FILES

Chapter 5

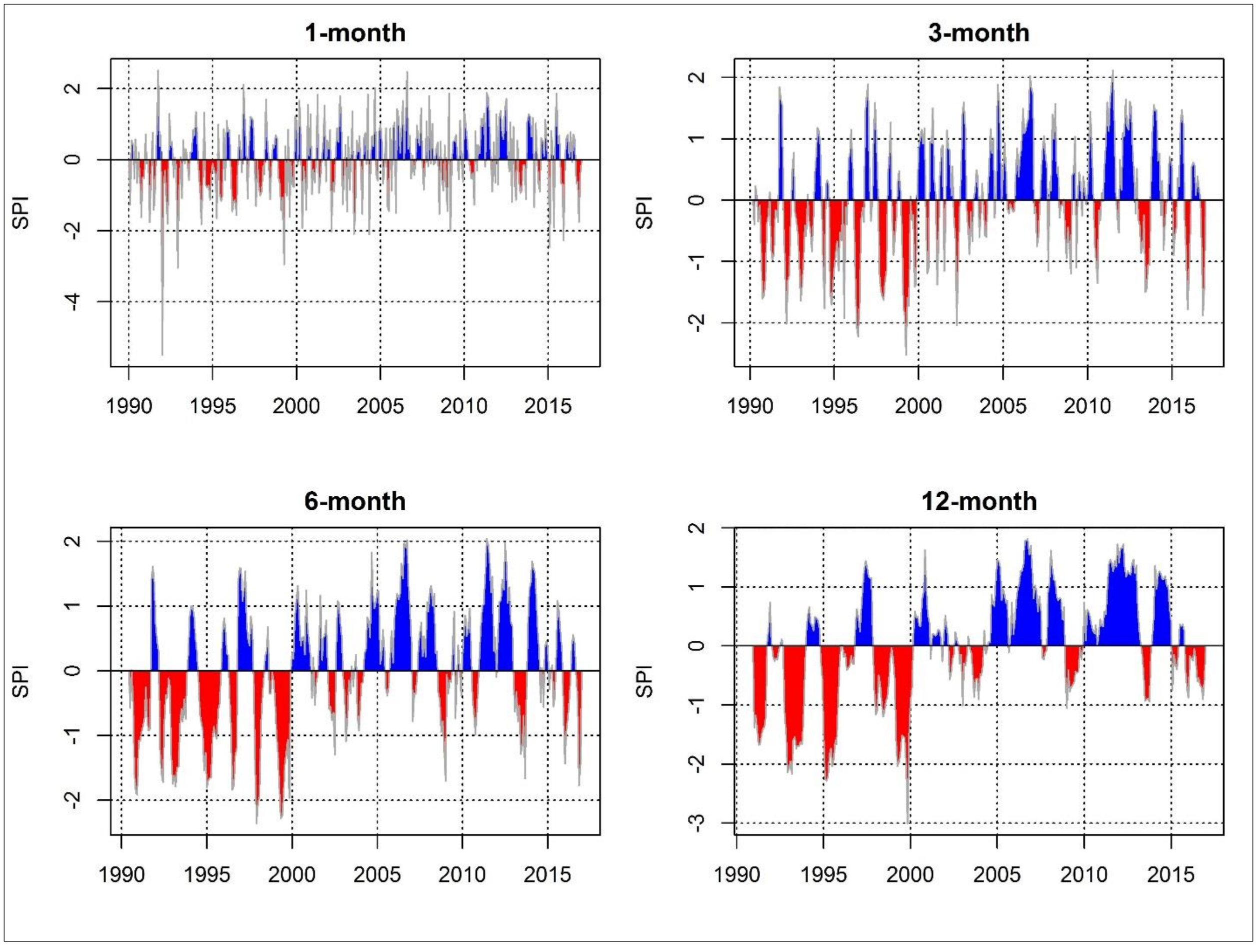

Figure 5-13: Drought indices quantified by the SPI in different timescale 1-, 3-, 6- and 12-month calculated using averages over the 4 stations in North West province.

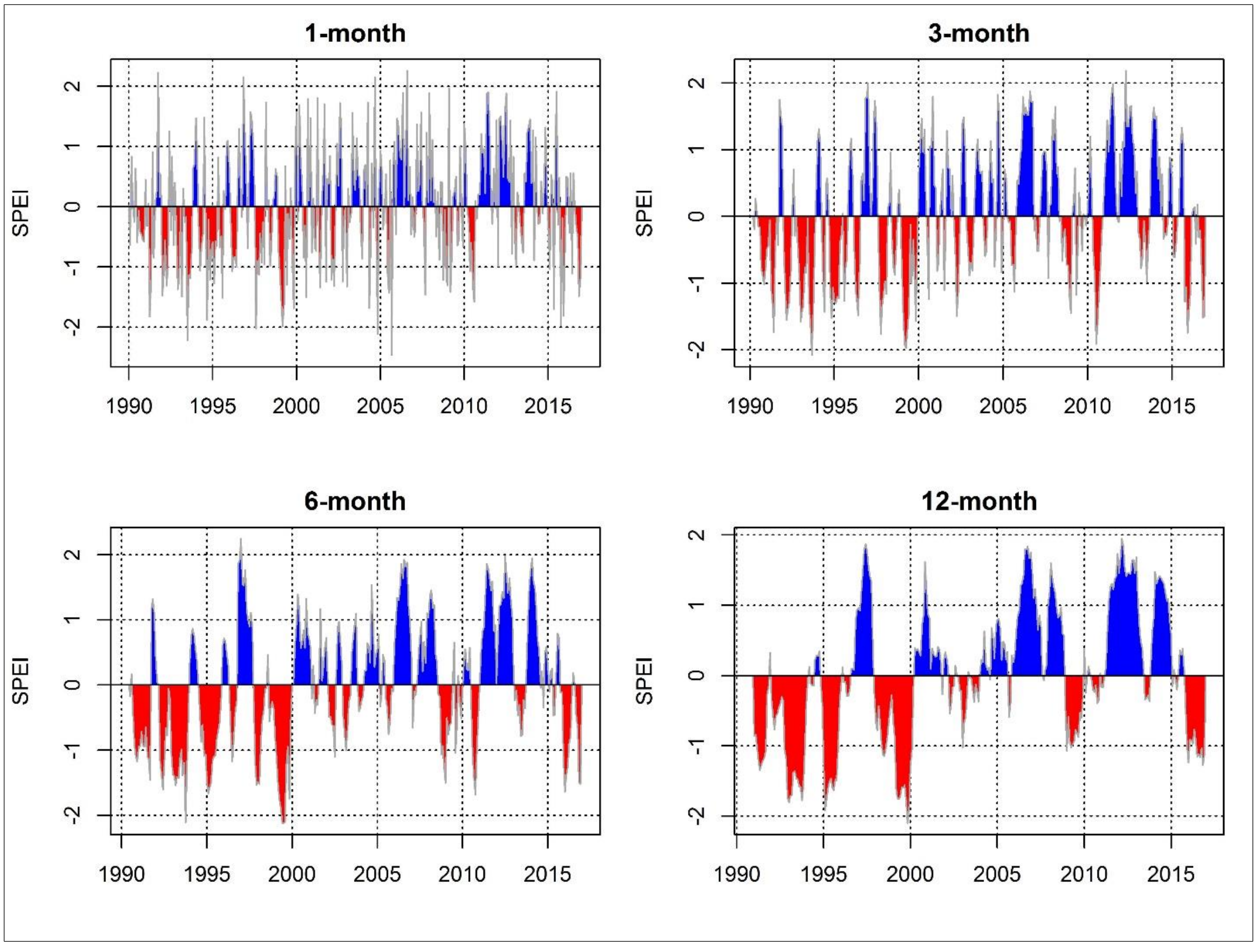

Figure 5-14: Drought indices quantified by the SPEI in different timescale 1-, 3-, 6- and 12-month calculated using averages over the 4 stations in North West province.

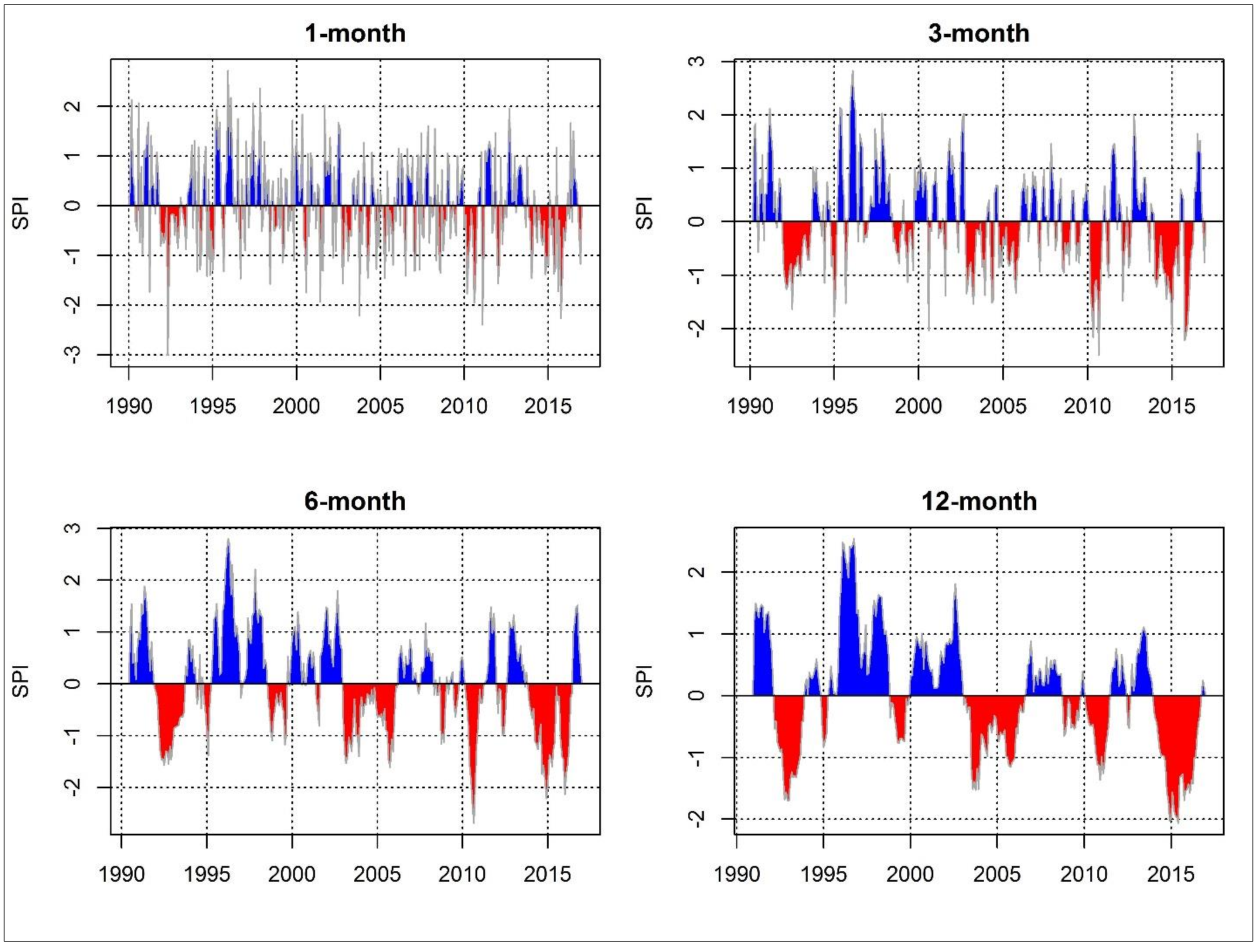

Figure 5-15: Drought indices quantified by the SPI in different timescale 1-, 3-, 6- and 12-month calculated using averages over the 4 stations in KwaZulu-Natal province.

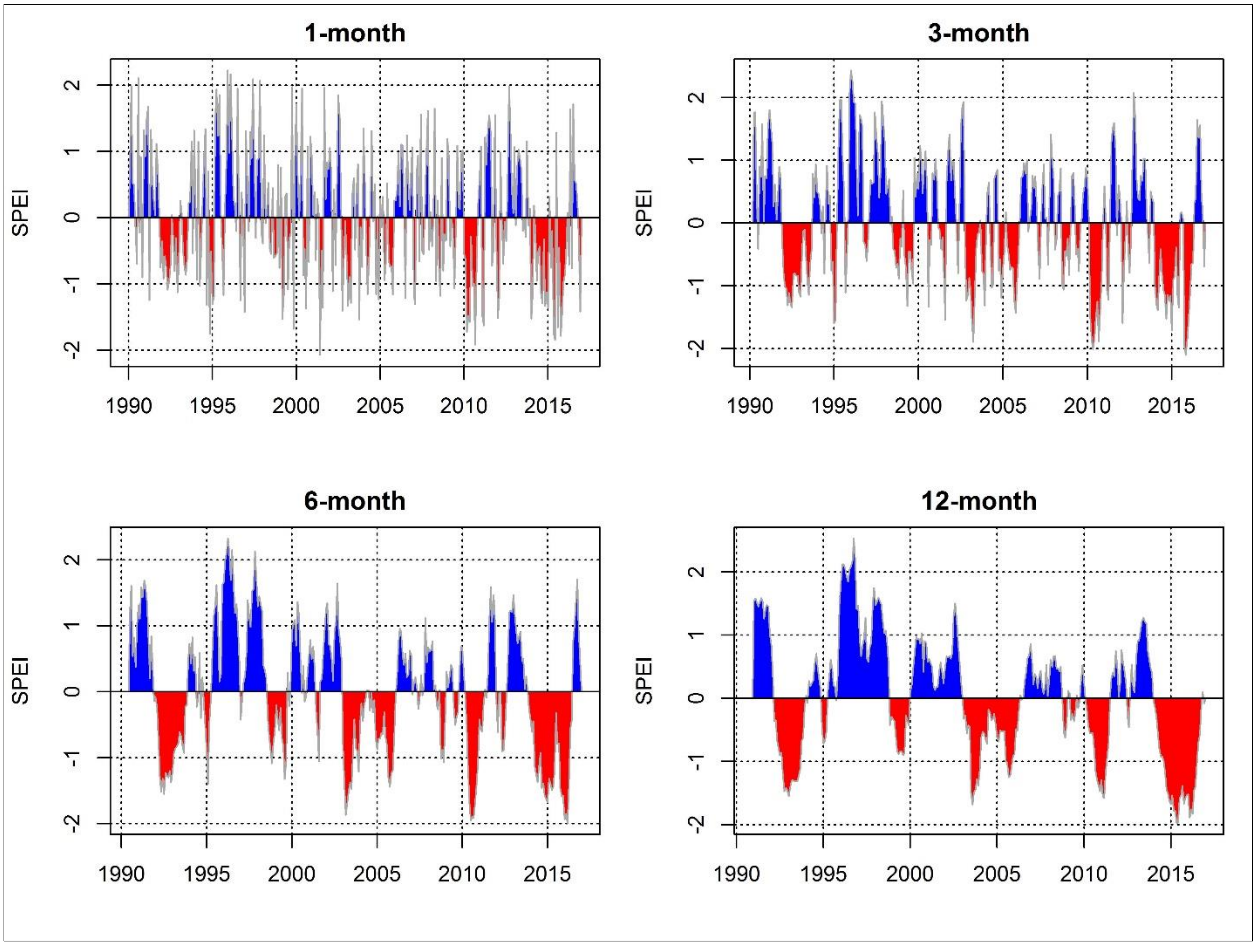

Figure 5-16: Drought indices quantified by the SPEI in different timescale 1-, 3-, 6- and 12-month calculated using averages over the 4 stations in KwaZulu-Natal province.

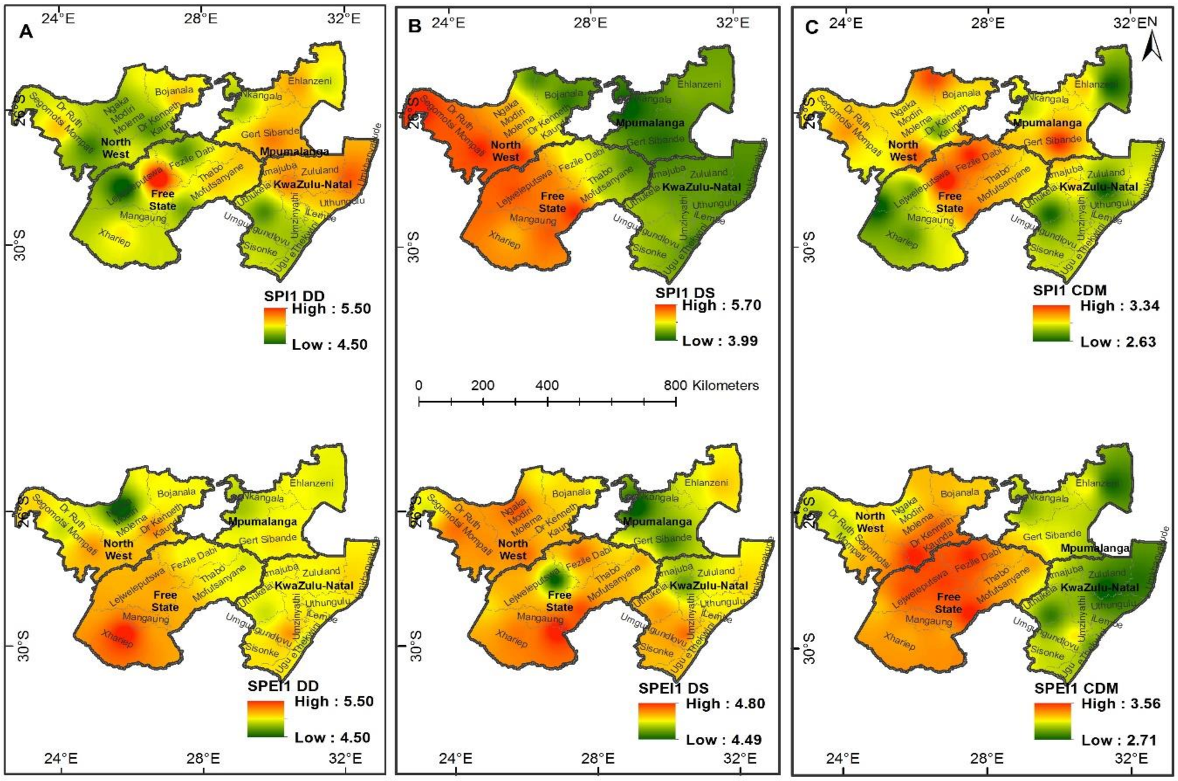

Figure 5-17: Spatial contrasts of the mean DMIs derived from SPI-1 (top) and SPEI-1 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM.

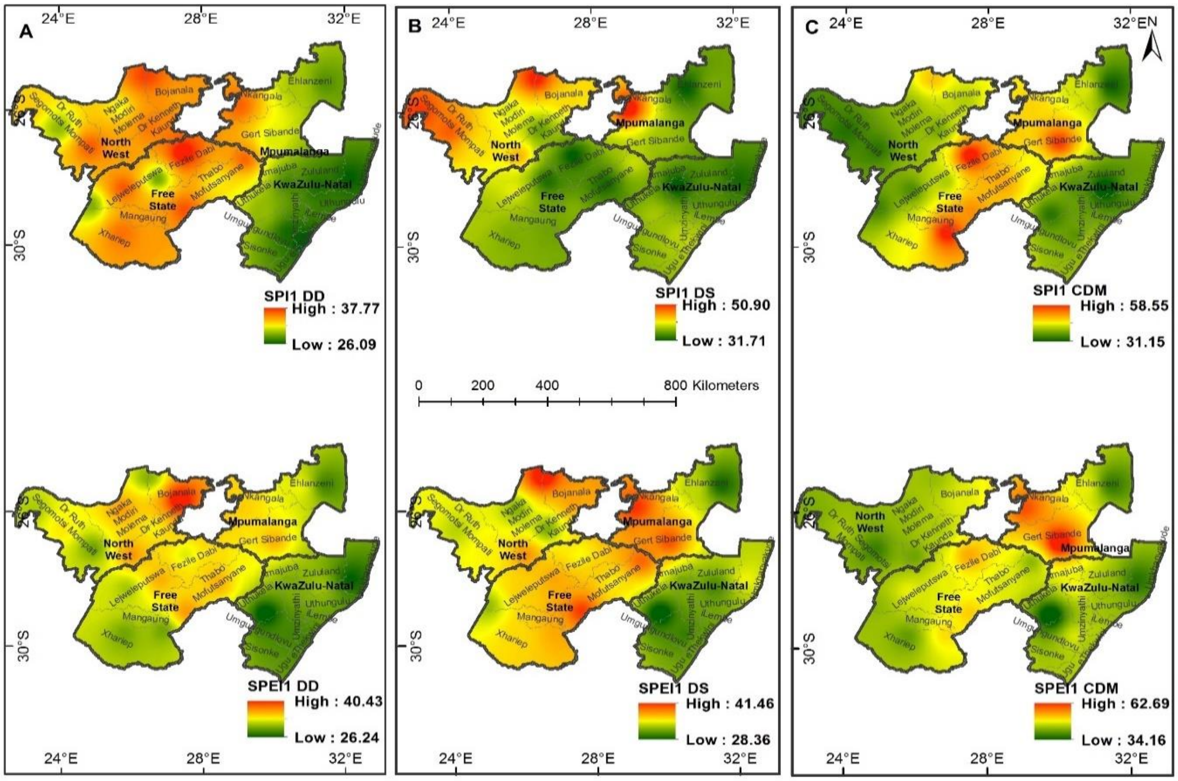

Figure 5-18: Spatial contrasts of the coefficient of variation (CV) of DMIs derived from SPI-1 (top) and SPEI-1 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM.

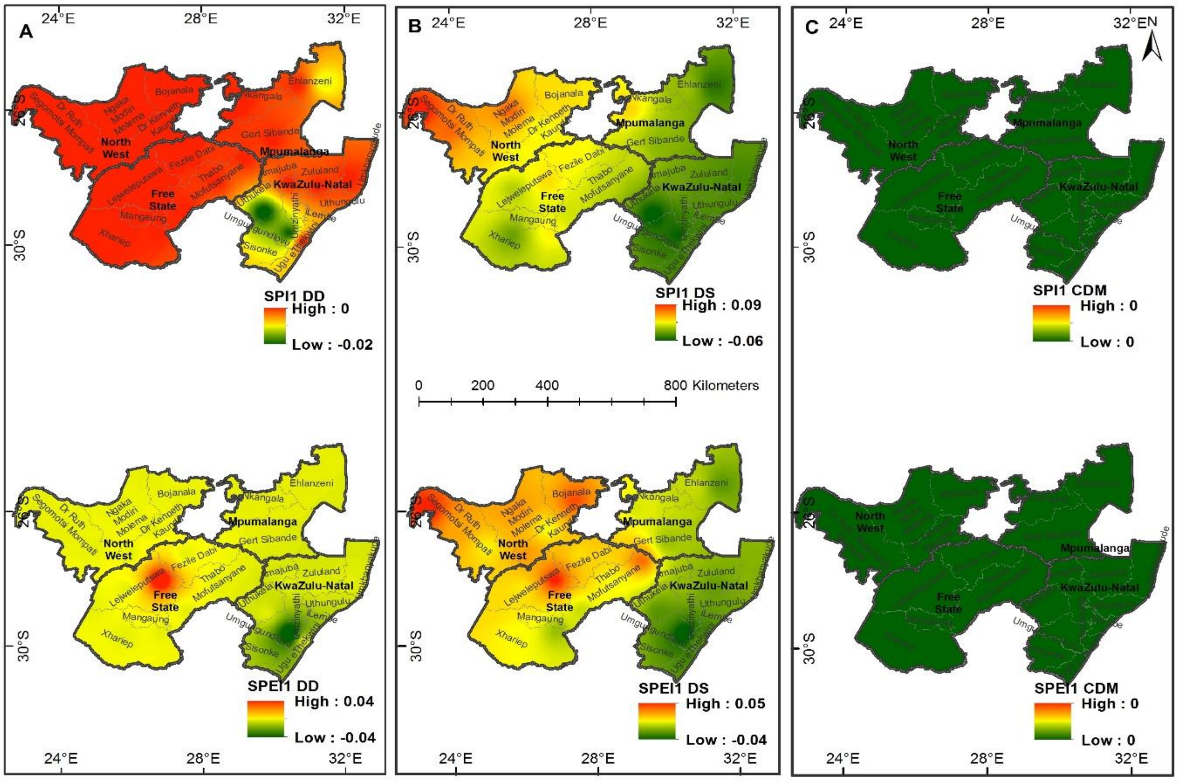

Figure 5-19: Spatial contrasts of the trends of DMIs derived from SPI-1 (top) and SPEI-1 (bottom): Panel A corresponds to DD while B and C correspond to DS and CDM.