CAUSALITY ANALYSIS AND PHYSIO-ECONOMIC IMPACTS OF CLIMATE CHANGE ON MAIZE PRODUCTION IN SOUTH AFRICA

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Submitted in fulfilment of the academic requirements of the degree

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NOVEMBER 2019

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The following publication forms part of the research presented in this dissertation.

Manuscript 1 – Chapter 3

Magodora T.L. and Baiyegunhi L. A time series analysis of the causality between climate change and maize production in South Africa. (Under review: *Heliyon*).

ACKNOWLEDGEMENTS

I want to thank;

The Almighty Father, for being good at all times.

My supervisor, Professor Lloyd Baiyegunhi, for your guidance, contributions, patience and constructive comments;

The NRF bursary funding, DAFF and SAWS for support and contribution towards making this study a reality;

My colleagues at the Department of Agricultural Economics (Office 336), your academic contributions is highly appreciated;

My family, Jeremiah Magodora, Dorothy Chiweshe, William Maguraushe and Mavis Makoni and the whole Magodora Family, for your unwavering support throughout the years.

The Gwena family and all other friends, God bless you.

ABSTRACT

Agriculture, as part of the human ecological footprint on climate change, has become a serious concern because climate change has an impact on agriculture. For instance, when crop production is considered, climatic elements are influenced by greenhouse gas emissions that come from agricultural activities such as the application of synthetic fertilizers, herbicides and pesticides, as well as the use of heavy machinery in modern crop production. This study analyzed the possible causalities between climatic variables and maize production in South Africa using time series data for the period 1924 to 2016. The analysis was done using VAR Granger causality analysis to ascertain if there are feedback loops between climatic elements and maize production in South Africa. The results from the Granger analysis suggest a bidirectional causality that runs between maize production and temperature. Rainfall alone was found not to be significant in influencing maize production but a combination of both temperature and rainfall affects maize production in South Africa. The results from variance decomposition of the future forecasts suggest a relatively large magnitude of impact (13.37%) of temperature on maize production in the 3rd year of the forecast with the highest effect of 27.43% in the 15th year of forecast. The forecasted impact of rainfall on the other hand remained relatively low (below 10%) throughout the forecast period. Continued current production activities (use of synthetic fertilizers and agricultural chemicals, for example) will affect climatic variables both in the short term and in the long term, and the effects of these changes in climatic elements on maize production will be realized in the long term as revealed by the variance decomposition result.

The study further investigated the impacts of global warming on maize production in South Africa using meta-analysis (for physical impacts) and the Ricardian analysis (for economic impacts). The meta-analysis made use of studies that investigated and reported percentage changes in maize yield owing to climate change in South Africa. The average estimated percentage change in maize yield was calculated from 34 studies using the bootstrapping sampling technique. Results from the meta-analysis suggest that maize yield will drop by more than 15% owing to temperature increase of about 2^0C to be realized between 2081 and 2100. The Ricardian analysis made use of time series data for the period 1987 to the end of 2018. The results from the Ricardian analysis also show that climate change is a significant threat to the South African maize industry, as it is estimated to lose an average of 38% of revenue owing to plus 2^0C warming. Given these outcomes, the study suggested the adoption of sustainable farming activities such as minimum tillage, balanced fertilization and biochar amendments at a much faster rate in order to ensure a sustainable increase in maize production, while at the same time reducing the human ecological footprint on climate change. The study also recommends the recognition of the agricultural sector as one of the sectors that should be targeted by the carbon emission reduction systems.

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LIST OF ACRONYMS/ABREVIATIONS

AIC	Akaike Information Criterion
AL	Agricultural labour
AM	Agricultural machinery
ARC	Agricultural Research Council
ARDL	Auto regressive distributed lag
CH_4	Methane
CO_2	Carbon dioxide
DAFF	Department of Agriculture, Forestry and Fisheries
ENSO	El Niño Southern Oscillation
FAO	Food and Agriculture Organisation
FARM	Future agricultural resources model
FPE	Final prediction error
GCM	General circulation model
GDP	Gross domestic product
GEM	General equilibrium model
GHG	Greenhouse gas
GLOBIOM	Global partial equilibrium model
GWP	Global warming potential
IAM	Integrated assessment model
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
LGVM	Log gross value of maize
LIRR	Log irrigation
(LM)	Lagrange Multiplier
MPO	Milk producers of South Africa
MPX	Maize production
M_tCO_{2e}	Metric tonnes of carbon dioxide emissions
N_2O	Nitrous oxide
NASA	Natural Aeronautics and Space Administration
NDP	National Development Plan
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PDO	Pacific decadal oscillation

PP	Phillips-Perron
PRC	Price
RFLL	Rainfall
SADC	Southern African Development Community
SAWS	South African Weather Services
SIC	Schwarz information criterion
STATS SA	Statistics South Africa
TMP	Temperature
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
USA	United States of America
VAR	Vector auto-regressive/auto-regression
VECM	Vector error correction model

Chapter 1
Introduction

1.1 Background

Climate change has been of serious concern since the beginning of the 19st century, threatening countries mainly in the sub-tropical regions. The world's climate varies from one decade to another, and a varying climate is natural and expected (Savitsky, 2017). However, it is believed that human industrial and developmental activities of the past two centuries have caused changes over and above the natural variations. These industrial and developmental activities include agriculture, which provides food for the growing population of the world. Literature has shown that climate change and agriculture are two entities that cannot be separated; however, their interaction has resulted into a negative impact on agricultural production and livelihood (Lobell and Burke, 2010; Lipper *et al.*, 2014; Nhemachena *et al.*, 2014; Mangani *et al.*, 2019).

According to Lipper *et al.* (2014), agriculture links with climate change through its greenhouse gas emissions that come from agricultural activities such as the use of fertilizers and other agricultural chemicals, bush burning, land clearing as well as other human activities. Moreover, most agricultural greenhouse gases are nitrous oxide (N_2O) and methane (CH_4) with carbon dioxide (CO_2) also being included if emissions from the use of machineries are considered. These greenhouse gas emissions cause a global warming, which is a term that denotes a gradual rise in the average temperature of the earth's atmosphere, causing a change in climate (Oduniyi, 2018). The increase in the greenhouse gases has led to an average increase in temperature by 0.74^{o}C since the beginning of the 19th century, causing some serious global warming according to the Intergovernmental Panel for Climate Change (IPCC) fourth assessment report of 2007.

On the other hand, climate change affects food production directly through changes in agro-ecological conditions and indirectly by affecting income growth and distribution (Schmidhuber and Tubiello, 2007). In this instance, climate change has affected and may continue undermining global agriculture in the 21st century, with crop production being one of the most affected (Ochieng *et al.* 2016). Predictions show that global crop production will fall by an estimated 2% to 6% per decade, which is significant given that the world population growth rate is around 1.08% per year (Little *et al.*, 2019; Rose *et al.*, 2019). As a result, climate continues to threaten humanity as it instigates food shortages and causes some social unrest, especially in countries that are underdeveloped and highly dependent on agriculture (Bellemare, 2015).

Most African countries are very dependent on rain-fed agriculture, which contributes about 30% of the gross domestic product (GDP) and employs almost 70% of the population on the continent; at the same time, it is the main safety net of the poor (Balcha and Macleod, 2017). Africa has already experienced various climate-related stress, including drought, floods and rainfall variability, among others (Adisa *et al.*, 2018). These stresses are mainly accompanied by low adaptive capacity, high sensitivity, exposure and vulnerability to climate change which makes the continent more vulnerable to changes in climate. According to Kang *et al.* (2009), the effects of climate stresses are mainly on crop production, especially maize in the arid and semi-arid areas of Africa. South Africa is one of the countries in the semi-arid region, and two-thirds of its land area receives less than 500mm of avera4ge annual rainfall (Adisa *et al.*, 2018).

Maize production covers 58% of the cropping area in the southern region of Africa, with South Africa (producing 50%) being the major producer in the region (FAO, 2018). Because maize is the staple crop of South Africa and of the whole Southern African Development Commission (SADC) region, any climatic influences on production will impact on food availability in the region. Furthermore, statistics show that maize production in South Africa contributes about R9.4 billion per annum to the economy; hence, any climate warming may threaten the economy in general.

Previous studies confirm that climate change will cause a decrease in maize yields. For instance, Akpalu *et al.* (2008) found that average maize yield will fall by approximately 4% as a result of a 10% reduction in rainfall. Surprisingly, a few proponents claim that climate change will result in some yield gains. In a study by Dube *et al.* (2013), it was suggested that there will be yield gains ranging between 5% and 25% for rainfed maize owing to temperature increase and a fall in rainfall amounts. As a result, this might cause confusion regarding whether a change in climate will result in some yield gains or yield losses. In this case, some farmers might consider the fact that climate change may result in yield gains, and thus continue with their farming activities that emit greenhouse gases and that might not be sustainable in the future. It is therefore important to assess some statistical relationships that exist between maize production and climate change in South Africa using time series data, and thereby assess the physio-economic impacts of climate warming. Climatic variables (temperature and rainfall) were used as a measure of climate change in this study. To attain these aims, the study firstly employed some Granger causality tests and used variance decomposition to assess and forecast the relationship between maize production and climate change. The physio-economic impacts were examined using two approaches, namely meta-analysis (for physical impacts) and Ricardian analysis (for economic impacts).

1.2 Research problem

Globally, future climate scenarios predict an increase in the frequency of extremely hot days, together with an increase in average global temperature (Fodor *et al.*, 2017). This trend has already been observed during the past decades, and has implications for global food production given the rise in population numbers. Between 2001 and 2011, greenhouse gas (GHG) emissions from crop and livestock production in Southern Africa grew by 14% (Lipper *et al.*, 2014). Moreover, on a global scale, statistics show that GHG emissions have increased by approximately 30% to 40% since the year 2000, with three-quarters of these emissions occurring in the Sub-Saharan countries. This is not a favourable condition, as GHG emissions aggravate climate disruption, thus affecting maize production negatively. Negative impacts on maize production therefore translate into some serious economic problems in a country like South Africa where maize is the staple crop and contributes a large to the economy given that maize exports contributed about R2.5 billion revenue in 2019 (DAFF, 2019).

The average annual temperatures in South Africa have increased by at least one-and-a-half times more than the observed global average of 0.65°C in the past 50 years (Ziervogel *et al.*, 2014). In addition, below average rainfall events have increased in frequency, hence leading to serious fluctuations in maize output; this situation is predicted to continue. According to the IPCC (2013), South African temperatures will rise by 2-6°C by 2081-2100, compared with 1986-2005. This will pose a threat to maize production in South Africa, and therefore more and more fluctuations in maize yields are expected.

The consequences of the variations in weather conditions have already been felt in South Africa, as it became a net importer of maize in the years 2015 and 2016 even though maize production in the country uses the most advanced technology in the region (Opara, 2017). Although there was a bumper harvest of 17.7 million metric tons in 2017, maize production was projected to fall in 2018 by the US Agricultural Department. According to estimates by FAO (2018), maize production in South Africa will decline by about 20% from yields of 2017 owing to unfavourable rainfall received in the farming season 2017-18. This decline in maize output can be assumed to have a significant impact on the South African economy as the GDP growth rate has fallen by 2.2%, with agriculture contributing negative 0.7% to GDP growth in 2018 (MPO, 2019). As highlighted by FAO (2019), this decline in maize is already being felt in terms of price as the price of maize has been increasing steadily at the rate of about 5% each month since February 2018 as shown in Figure 1.1. This issue is, therefore, creating some challenges for the consumers as their disposable incomes are being reduced; consequently, some people may continue to experience the problem of food shortages especially at the household level.

Based on the above discussion, some feedback loops therefore, seem to exist between maize production and climate change; this has serious consequences for the economy, hence this study seeks to answer the following research questions.

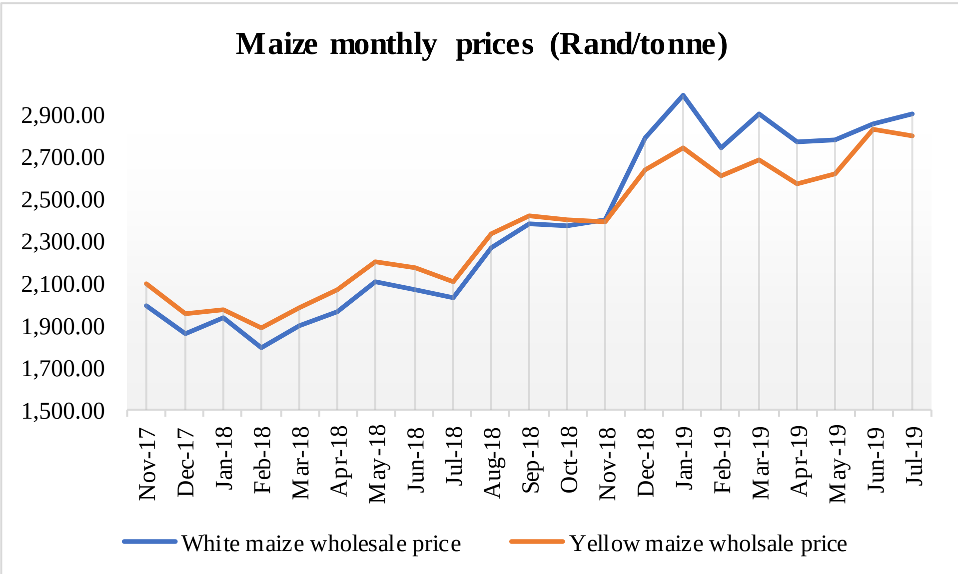

Figure 1.1: South Africa Maize monthly prices (November 2017 – July 2019)

Source: *FAO (2019)*

1.3 Research questions

1. What is the direction of causality between climate change and maize production in South Africa?
2. What is the physio-economic impact of climate change on maize production in South Africa?

1.4 Objectives of the study

The broad aim of this study is to undertake a causality analysis regarding the physio-economic impacts of climate change on maize production in South Africa. The specific objectives are to

1. Examine the linkages between climate change and maize production in South Africa, and,
2. Examine the physio-economic impacts of climate change on maize production in South Africa.

1.5 Justification of the study

Maize production in South Africa is dependent on weather conditions (temperature and rainfall). For instance, the optimum maize germination temperature is between 20°C and 30°C, while the moisture content of the soil should be approximately 60% of soil capacity (Du Plessis, 2003). Any recorded average temperatures that fails to fall in the above-mentioned range would cause some major challenges for the production of maize. Since variations in weather conditions are mainly determined by climate change (Savitsky, 2017), it means climate change is, therefore, a major challenge for maize production. Looking at some of the causes of the change in climate, it has been discovered empirically that agriculture plays a significant role through the emission of greenhouse gases such as nitrous oxide and methane (Pryor *et al.*, 2017). As these greenhouse gases trap sunlight energy, this would lead to serious warming that is going to influence crop production, thus making a vicious cycle of problems. This will therefore also threaten the country's water resources, food security, health, infrastructure and ecosystem services and biodiversity, and these could transform into critical challenges for development. There is therefore important to carry out a study in South Africa to identify the nature of the linkages so that policy makers may be able to devise sustainable strategies to lessen the effects of climate change. It is also important to quantify the effects of climate change on maize yield and the maize industry in general to help in formulating effective and efficient mitigation and adaptation practices.

1.6 Limitations of the study

Similar to other studies, this study faced some limitations, therefore the results produced need to be interpreted with caution. It was good to include a variable for carbon emissions in the analysis of the first objective, however, data for carbon emissions which span for a longer period is not available for South Africa hence the faced some data limitations. The problem of data scarcity also influenced the analysis of the second objective where the study employed interpolation and extrapolation of data methods as well as bootstrapping to cater for this issue. Although there were some data issues in the study, the study objectives were achieved.

1.7 Chapter overview

Chapter 1 presented the research problem, objectives and justification of the study. This is followed by Chapter 2 that presents the literature related to the study. This is divided into sections, including an overview of climate change and variability, greenhouse gas emissions from agriculture, the impacts of climate change on maize production, as well an overview of the methods used to estimate the impacts of climate change on agricultural production. Chapter Three examines the causalities between maize production and climate change, and Chapter Four considers the physio-economic impacts of a change in climate on maize production. The study concludes with Chapter Five, which consists of the conclusions reached by the study, recommendations, limitations and suggestions for further studies.

Chapter 2
Literature review

2.1 Introduction

This chapter reviews the literature on climate change and agricultural production. The first three main sections discuss the basic elements of climate change, including its causes and the influences on agriculture, with specific reference to South Africa. A review of how agricultural activities lead to a change in climate, as well as how the changing climate affects crop production, is also included. The last two main sections discuss the literature on the relationship between climatic variables and crop production and the impacts of climate change on agriculture respectively. The models (Granger causality analysis and the Ricardian model) used for this study were adopted from the empirical literature provided in the last sections of this chapter.

2.2 Climate change and climate variability

There is generally confusion between climate change and climate variability; therefore, it is important to understand the two concepts. Climate change is defined as the alterations to the earth's atmosphere that occur over long periods, that is, from decades to millennia (Savitsky, 2017). It is normally referred to as anthropogenic, meaning that it occurs as a result of human activities such as industry and agriculture that lead to greenhouse gas emissions. IPCC defined it as a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity. Lineman *et al.* (2015) defined climate as a change in global or regional climate patterns, in particular a change apparent from the mid to late 20th century onwards and attributed to the increased levels of atmospheric carbon dioxide arising from the use of fossil fuels. However, climate variability as defined by IPCC defines is any change in climate over time, whether due to natural variability or as a result of human activity. Savitsky (2017) defined climate variability as the fluctuations in weather elements (for example, temperature and rainfall) around the average without causing the average itself to change. Scientists normally refer to time periods ranging from months and up to 30 years. Climate variability is believed to be mainly driven by natural causes such as the El Niño southern oscillation (ENSO) and the Pacific decadal oscillation (PDO) in South Africa (Wang *et al.*, 2011). However, increased frequency of climate variability is one of the signs that the climate is changing, therefore the two have a high correlation. It can therefore be seen that besides natural forces that influence climate variability, human activities also play an important role in climate variability. As mentioned previously, the anthropogenic forces include agricultural activities such as crop production, which involve the use of synthetic fertilizers, agricultural chemicals and land clearing, thereby leading to an increase in the amount of greenhouse gases in the atmosphere (Lipper *et al.*, 2014).

The sun is known as the primary source of energy for the earth's climate. Bright surfaces on earth such as ice and clouds reflect some of the sunlight back into space, whilst the rest is absorbed by the surface and the atmosphere and re-emitted as heat (infrared radiation). Climate change therefore results from any disturbances in the balance of the incoming and outgoing energy, and this is mainly caused by human activities that emit greenhouse gases. Although greenhouse gases play a significant role by making life on earth possible, too much of these gases will bring about a change in climate that has serious consequences for plant growth. The process of the earth's climate and how it is affected by human activities is illustrated by the Lovelock's Gaia theory.

2.2.1 The Gaia theory

Lovelock (2003) views the earth's planet as a self-regulating organism, consisting of living and non-living organisms that work as components and partners of a single body that maintains the earth as a habitable planet. He viewed the earth as a Gaia[1] that consists of three characteristics. The first characteristic is the tendency to keep constant conditions for terrestrial life forms. This tendency predates the arrival of humans, and Lovelock argues that if the planet's natural equilibrium is maintained, the planet will continue to survive. Secondly, he views the earth as having vital organs both in its core and periphery. Human interference with these vital organs (for example, agriculture), will determine if the planet will survive or not. The third characteristic of the Gaia is the way in which the planet obeys the laws of cybernetics, which means the earth can self-regulate and correct itself in the event of any imbalances.

[1] Lovelock (2010) defined the Gaia as the personification of the earth.

Lovelock, J. 2003. Gaia: the living Earth. *Nature* 426(6968): 769.

However, the planet is increasingly facing pressures that may disrupt its ability to self-regulate and recover from factors that cause an imbalance in its systems (Lovelock, 2003). Agricultural activities (are regarded as one of the factors that cause an imbalance to the systems in the Gaia through the emissions of GHGs such as nitrous oxide, methane and carbon dioxide (Lipper *et al.*, 2014). Moreover, as mentioned previously, these GHGs absorb terrestrial radiation, thus leading to a global rise in temperature through the process of global warming. As a result, this causes a change in climate that has severe consequences on agricultural production and to the economy as a whole.

2.2.2 Agriculture as a driver of climate change

As stated by the Gaia principle, the human footprint through agricultural activities like maize production have a negative impact on the health of the earth (Le Quéré *et al.*, 2017). Agricultural actions such as deforestation increased dependency on agro-chemical for both crop and animal production (chemical fertilizer, herbicides, insecticides, vaccines and antibiotics, and biotechnology, among others) stimulate the rate at which the climate is changing (Adomako and Ampadu, 2015). The 2017 emissions gap report by the United Nations Environment Program (UNEP) supported this assertion, stating that some agricultural practices such as those already mentioned, lead to greenhouse gas emissions, which in turn lead to climate warming. For instance, conventional tillage is believed to cause soil compaction, which reduces the carbon sequestration of the soil, thereby contributing to anthropogenic emissions of carbon dioxide (Le Quéré *et al.*, 2017; Pryor *et al.*, 2017).

Crop production is associated with many of the activities that increase the agricultural footprint. Globally, crop production occupies 40%-50% of the total land area of the earth, and this accounts for 10%-12% anthropogenic GHG emissions (Le Quéré *et al.*, 2017). According to Barker *et al.* (2007), a complete life cycle of agricultural products can increase agricultural emissions by 26%-30% of the global anthropogenic footprint. Likewise, Russell *et al.* (2014) found that about 6 billion tonnes of greenhouse gases were emitted by crop farming in 2011, which comprises about 13% of total global emissions, thus making the agricultural sector the world's second largest emitter after the energy sector.

As a result of the above, many debates have risen. For instance, UNEP suggested in 2013 that the adoption of zero-tillage by farmers across the globe will reduce the contribution of agriculture to greenhouse gas emissions. However, Powlson *et al.* (2014) did not agree with the idea of zero-tillage, citing the lack of capacity of this activity in reducing the impact of climate change. Moreover, it was highlighted that no-tillage might increase or decrease nitrous oxide emission that have positive or negative impact on climate change. Subsequently, proponents like Powlson *et al.* (2014) advocate more tillage to reduce the socio-economic impacts (such as decrease in agricultural GDP, agricultural unemployment, and food insecurity, among others) of climate change.

Further suggestions highlighted that agricultural influence on climate change arises because of its indirect influence of the emissions of greenhouse gases. Wood *et al.* (2004) highlighted that indirect activities like input production and transportation of agricultural products such as grains also lead to greenhouse gas emissions. In this scenario, the production of nitrogen is seen to be energy intensive, therefore, it leads to more emissions that were indirectly attributed to the agricultural sector. In addition, more emissions from agriculture are ascribed to energy demand for irrigation and the demand for fuel to operate agricultural machinery on farms (Plevin *et al.*, 2015). These energy and fuel demands therefore led to the conclusion that agriculture is one of the significant sources of greenhouse gas emissions, which might explain the increase in warming that the earth is currently experiencing (Camargo *et al.*, 2013). This assertion was supported by Gifford (1984, as cited by Camargo *et al.* (2013), who classified agricultural emissions into primary (fuel for machinery and operations), secondary (production and transportation of inputs) and tertiary (raw materials to produce items such as machinery and buildings) sources that lead to dangerous agricultural emissions. Thus, agriculture contributes enormously to greenhouse gas emissions. However, the agricultural sector was overlooked, as it was not mentioned at the Paris agreement as one of the sectors that should pay carbon taxes (Rogelj *et al.*, 2016). In its national development plan, South Africa is also implementing a carbon tax regime which does not include agriculture (National Treasury, 2014).

2.2.3 Greenhouse gas emissions from agriculture

Scientific findings are now showing that these agricultural emissions mainly come in the form of CH4 and N_2O. Cattle belching CH4 and the application of synthetic fertilizers and wastes (N_2O) to soils form the most significant sources of greenhouse gas emissions, comprising about 65% of agricultural emissions globally (Russell *et al.*, 2014). Agriculture is also associated with land use changes that occur in conjunction with deforestation; C_2O absorbers are then reduced, thereby increasing the amount of carbon dioxide in the atmosphere. Although crop production may benefit from rising C_2O, it also, however, increases the potential for abiotic stresses such as heat waves and ultraviolet B radiation that will pose a challenge for plant growth (Singh *et al.*, 2015), thus threatening maize production.

C_2O is the main human-made gas, and it accounts for 76% of global emissions. However, agricultural emissions are dominated by CH4 (from ruminants and manure) and N_2O (from fertilizer and animal excrement), and contribute 16% and 6% respectively towards human-made warming (Russell *et al.*, 2014). While there is much less CH4 and N_2O in the atmosphere, as outlined in IPCC reports, these gases have different capacities to trap heat. As a result, they are assessed using global warming potential (GWP), which compares the ability of 1kg of each gas to trap heat over a 100-year time horizon. The GWP measure suggests that CH4 has 25 times the warming potential of CO_2, and N_2O is 298 times higher than C_2O (NASA, 2013). As a result, agricultural emissions are therefore a serious threat to the climate.

Carbon dioxide absorbs infrared wavelengths ranging from 4.2 to 4.8mm, whilst Methane and nitrous dioxide both absorb radian in the range of 7mm to 12mm each (Modest, 2013). The concentration of these gases in the atmosphere determines how much heat is trapped in the atmosphere; as a result, too much greenhouse gas leads to a rise in global temperature through global warming. The rise in temperature will, in turn, affect the amount of rainfall received, thus impeding crop production, resulting in some serious economic effects.

Several studies have been carried out concerning agricultural production emissions of greenhouse gases. In China's Henan Province, Su *et al.* (2017) investigated the trajectory, decoupling statuses and driving forces of agricultural carbon emissions. They analysed the relationship between carbon emissions and economic growth using the decoupling elasticity model and the Logarithmic Mean Divisia Index technique. Their results show that agricultural emissions grew by an average of approximately 0.65% from 1999 to 2014.

Vetter *et al.* (2017) found that agriculture is a significant source of greenhouse gas emissions globally when they carried out their study in India. In their study, they calculated greenhouse gas emissions associated with the production of primary food commodities using the cool farm tool. Their results suggest that the production of cereals emits less, thereby identifying livestock and rice production as the leading emitters of greenhouse gas emissions in India.

Some proponents, however, do not agree with the fact that agriculture is of significant concern in terms of greenhouse gas emissions. McGee (2015) investigated if organic farming can reduce greenhouse gas emissions from agricultural production in the United States of America (USA). To do this, they interpreted the relationship between the rise in organic agriculture and greenhouse gas emissions from agricultural production. The constructed two-time series fixed-effects panel regressions were used to generate the interpretations. The findings from their study state that there is no correlation between organic production and the reduction of greenhouse gas emissions in the USA. In contrast with Vetter's findings, McGee (2015) study suggests that the contribution of agricultural production to greenhouse gas emissions is not significant.

However, despite some of the above disagreements in the literature, a number of researchers are advocating some agricultural emission reduction strategies. For instance, Zhang *et al.* (2016) conducted a study that involved a two-year field experiment in assessing whether a high yielding, but low greenhouse gas emissions system, could be developed. Their study was set to identify if the combination of balanced fertilization and biochar amendment in rainfed farmland in the Northern region of China could lead to a system of higher yields and low greenhouse gas emissions. The results from this study suggest that balanced fertilization is useful in maintaining high maize yield and reducing greenhouse gas emissions that influence climatic elements.

2.2.4 Atmospheric influence of greenhouse gas emissions

Evidence of the influence of increased atmospheric GHG concentrations on the world's weather is widespread, leading to some effects on the climatic variables. The earth's surface temperature has grown by 0.85 (+/- 0.20)°C between 1850 to 2012, and intensified melting of glaciers and ice sheets has resulted in rising sea levels 0.19 (+/- 0.02)m between 1901 and 2010 (IPCC, 2013). Ummenhofer and Meehl (2017) highlight that extreme climate events affecting Europe, for example, are now more frequent, resulting in extreme precipitation and 23 severe warmth activities observed. Consequently, it is clear that the emission of greenhouse gases has a significant influence on the amount of rainfall received in a region, which then alters the agricultural output.

2.2.5 Agricultural greenhouse gas emissions in South Africa

According to the literature (Wang and Huang, 2005; Le Quéré *et al.*, 2015; Le Quéré *et al.*, 2017), no greenhouse gas emissions have been published for croplands in South Africa. However, greenhouse gases have been estimated on a national scale (Wang and Huang, 2005).

Tongwane *et al.* (2016) established the greenhouse gas profiles of field crops in South Africa, and determined that cereal crop production accounts for 68% of national field crops greenhouse emissions; maize was amongst the highest commodity emitters. South Africa is therefore classified in the group of countries that contribute 56% of emissions from crop production (Vetter *et al.*, 2017).

In the context of SADC, agricultural emissions are mainly attributed to agricultural activities in countries like South Africa, Angola, Madagascar, Zambia, Mozambique, Botswana, and Zimbabwe. In all these countries, enteric fermentation, especially of maize, is among the top three emitting agriculture subsectors. Figure 2.1 shows SADC highest agricultural sector greenhouse emitters, with South Africa dominating the high emitters with greenhouse gas emission around 30 $MtCO_2e$ over the period 1990 to 2011.

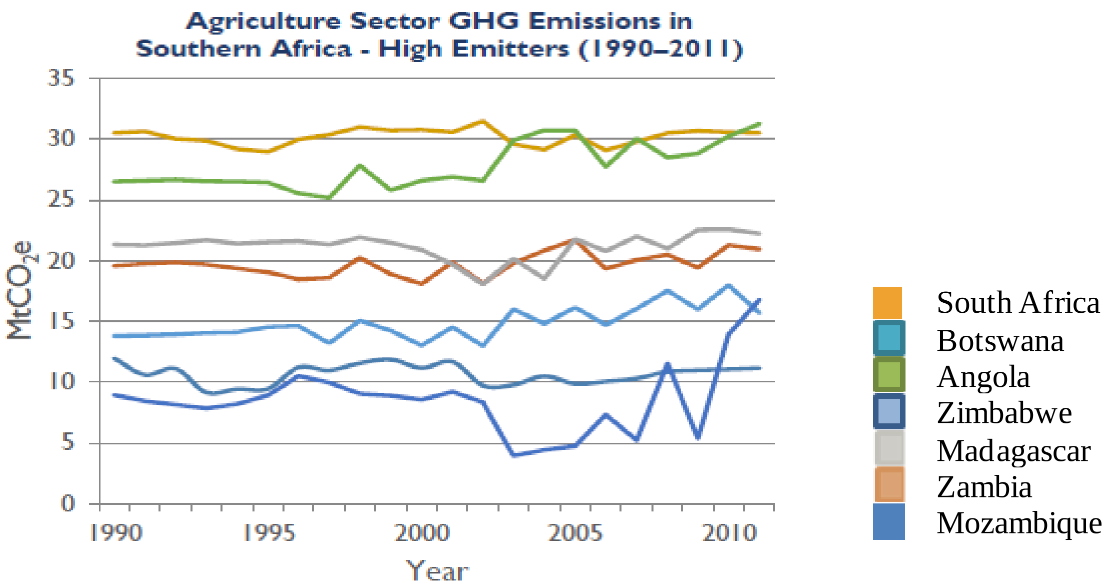

Figure 2.1: Agricultural sector GHG emissions in SADC-high emitters (1990-2011)

Source: USAID (2012)

As shown in Figure 2.1, South Africa has managed to maintain its greenhouse gas emissions around 30 $MtCO_2e$, though it remains on top of the high emitters in the region except for 2002, 2003, 2004 and 2010 when Angola exceeded it.

Owing to the emissions of greenhouse gases, there is some evidence of national and local variations in the temperature and rainfall climatology of South Africa over the past five decades (Ziervogel *et al.*, 2014). This evidence is grounded on numerous analyses of the weather station data of the South African Weather Service (SAWS) and the Agricultural Research Council

(ARC) as well as internationally developed and maintained climate data sets such as World Bank data.

2.3 Climate change in South Africa

This section outlines the major changes in the climate of South Africa by looking at the historical temperature and rainfall patterns, as well as the effects of these patterns on maize production.

2.3.1 Historical temperature and rainfall trends in South Africa

Studies of historical climate trends have been steadily growing during the last decade, given the increasing concerns about anthropogenic induced global warming and climate change. For instance, MacKellar *et al.* (2014) modelled trends in rainfall and temperature for South Africa, and found a statistically significant decrease in rainfall combined with a statistically significant increase in temperature throughout the country. Intense warming trends have been observed in the drier western parts of the country (Northern Cape and Western Cape) and in the northeast in Limpopo and Mpumalanga, extending southwards to the east coast of KwaZulu-Natal. In these areas a rate of warming of about 2^0C per century or even higher was observed, and this is regarded to be more than twice the global rate of temperature increase (Rogelj *et al.*, 2016). Figure 2.2 shows the South Africa average annual temperature over the period 1901-2015 with an escalating trend of about 2^0C, that is from above 16^0C to above 18^0C over the period.

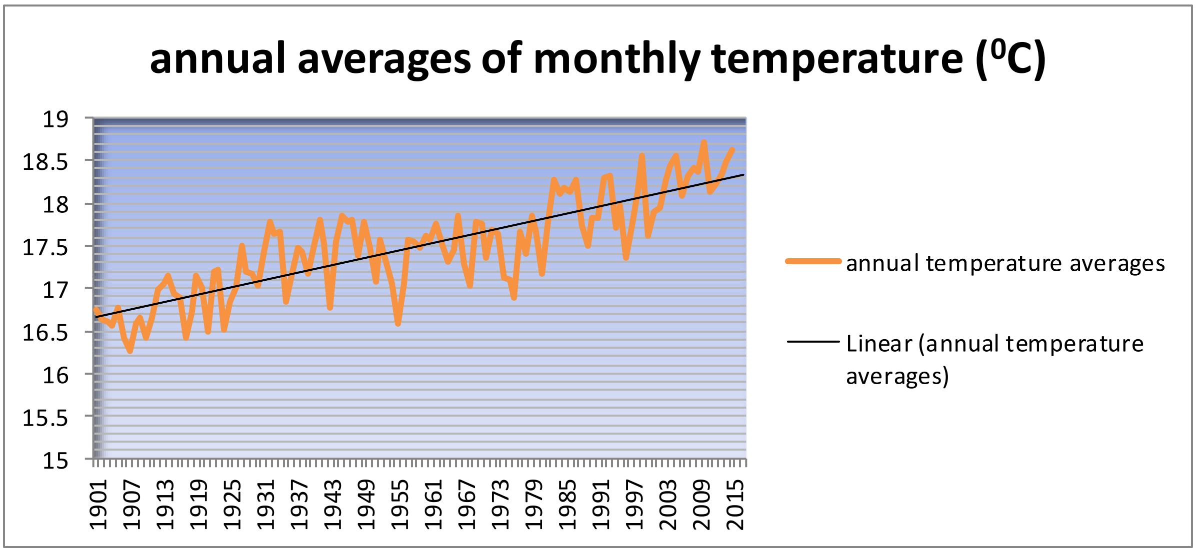

Figure 2.2: South Africa average annual temperatures (1901-2015)

Source: *World Bank (2017)*

The wettest regions are the eastern provinces (Mpumalanga, Free State, Gauteng and Kwazulu Natal) with an average annual rainfall of up to 900 mm. The average annual rainfall in the central area of the country is around 400 mm, decreasing west ward to less than 200 mm, leaving the western and north western regions of the country with semi-desert and desert type climates. An exception to the overall rainfall pattern of South Africa 's climate is the south-western part of the Western Cape province. This area is a typical Mediterranean climate with the rainfall occurring during the winter period, coming in from the Atlantic Ocean. The average annual rainfall for this area is 515 mm. Looking at the historical data of annual rainfall for South Africa at national level, it shows that there are various fluctuations in the annual averages of monthly rainfall, oscillating around 40% with a high of 56% in 1976 and a low of 26% in 1992 (World Bank, 2017). However, the trend shows that there is no significant change over the period 1901-2015 (see Figure 2.3).

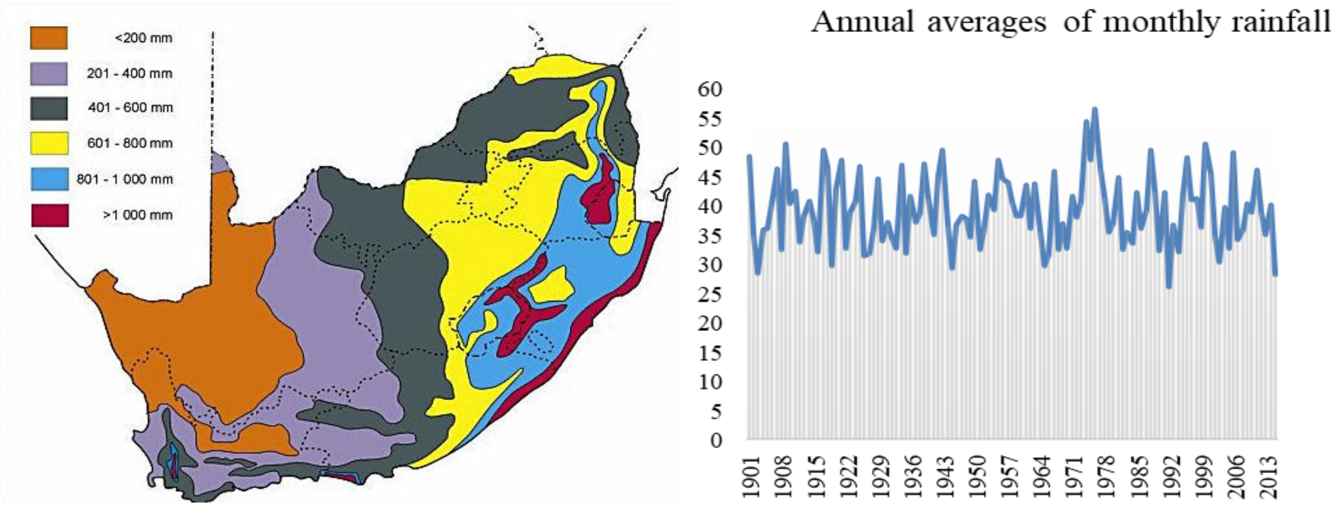

Figure 2.3: Map of rainfall distribution and chart of annual average rainfall (%) of South Africa (1901-2016)

Source: *World bank 2017*

The fact that increased frequency of extreme climate events is evidence of a changing climate implies a threat to South Africa. There is evidence that severe weather events in South Africa are increasing, with heatwave conditions found to be more likely, the duration of dry spells increasing slightly, and rainfall intensity increasing. Literature supports this assertion by noting that changes in extremes have been observed since 1950, and there is evidence that some of these changes are a result of anthropogenic influences (IPCC, 2015). Moreover, it can be noted that until the 2015/16 farming season, South Africa had largely avoided the adverse effects of El Niño conditions since the 1991/92 farming season (UNFCCC, 2017). Above-average rainfall over the past two decades has limited extreme drought conditions in South Africa and the region (Pryor, 2017). As a result, flooding and storm conditions have featured more prominently as extreme events rather than drought until 2014. The 2^0C rise in temperature observed can be attributed to this cause. Warmer temperatures have an impact on the plant during the reproductive stage of its development, especially in crops such as maize and wheat (Hatfield and Prueger, 2015). Literature also highlights that water deficits increase the effects of temperature and South Africa is regarded as one of the water-scarce countries in the world (Müller *et al.*, 2011).

2.3.2 Trends of maize production during climate change in South Africa

In general, the value of agriculture followed the rise in the GDP between the period 1946 and 2004, but experienced some dips in the 1980s and the early 1990s (Greyling, 2012). The reductions in GDP occurred in conjunction with the droughts mentioned above. The contribution of agriculture to GDP, however, fell within the same period. The adverse climate trends can explain this decrease in the agricultural contribution to the GDP. However, some explanations can be derived from other sectors that increased their contributions to the GDP. To accurately assess the extent of climate trends in South Africa it is, therefore, essential to use not only the value of the agricultural GDP, but also the trends in the production and harvest of critical crops such as maize.

The total acreage under maize fell during the period 1966 to 2004, and total production experienced an irregular cycle with extreme lows in the early 1980s and 1990s. The plummet in total production is a further reflection of the fall in total acreage rather than in yield; that is, maize yield did not change significantly over the period. The slight fall in maize production shows that there is an appropriate adaptation in the sector, such as the improved use of inputs. However, the decrease in the area under maize may indicate that some areas, especially in the arid agro-ecological zone, may be becoming too hot for the crop.

From the above, it is, therefore, possible to deduce a clear link between temperatures and land area under crops, but not a similar link between precipitation and land area under crops. Higher temperatures over the period may have made some areas, especially the arid areas, less suitable for field crops, which is one reason why the total land area for maize has declined, particularly since the 1980s. But it can be observed that, despite the decrease in total area planted by crops in response to higher temperatures, the yields for each of these crops have not changed significantly over the years, and total production has not seen a significant reduction

(Agricultural Research Council, 2018). What one can conclude is that the various adaptation methods that farmers are using across the country may be helping to maintain the levels of production despite the increased temperatures and the high variability in rainfall. Another important conclusion is that Climate change may not have any negative effect on maize production in SA. However, a closer look at these adaptation methods is needed as some of them might be leading to dangerous greenhouse gas emissions, thereby warming the climate.

2.4 Overview of the linkages between climatic variables and agricultural production

Some recent literature (Amikuzino and Donkoh, 2012; Igwe, 2013;Boansi 2017) have concluded that the agricultural footprint on climate change is becoming more severe as countries try to meet rising food demand owing to the increase in population around the globe. The South African population has increased from 51,6 million in 2010 to 58.8 million 2019 (Stats SA, 2019). As a result of this growth, efforts are being made to increase agricultural output so that the level of food security in the country will remain stable.

Pryor *et al.* (2017) studied the impact of agricultural practices on energy use and greenhouse gas emissions for South African sugarcane production using the life cycle assessment. Their results show that harvesting green cane reduces energy inputs and greenhouse gas emissions by 4% and 16% respectively in both irrigated and non-irrigated regions. Mechanization was found to have effects on soil compaction, and stool[2] damage thus results in lower yields and proportionally higher energy input and greenhouse gas emissions.

However, some literature does not agree with the results of Pryor *et al.* (2017). Although not as recent, Valin *et al.* (2013) investigated the effects of crop yield and livestock feed efficiency scenarios on greenhouse emissions from agriculture and land use change in developing countries. They used the global partial equilibrium model GLOBIOM. Their results confirm that yield increase could mitigate some growth in agriculture-related emissions over the next decades. Combining productivity increase in the two sectors appeared to be a most efficient way to benefit both food security and reduce emissions.

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[2] Refers to the remaining part of a monocot (for example sugarcane) crop after ratooning. Roge *et al.* (2016) defined ratooning as a method of harvesting a crop which leaves the roots and the lower parts of the plant uncut to give a new shoot (also known as a stubble) from the base of the plant.

Rogé, P., Snapp, S., Kakwera, M. N., Mungai, L., Jambo, I. & Peter, B. 2016. Ratooning and perennial staple crops in Malawi. A review. *Agronomy for Sustainable Development* 36(3): 50.

In addition, Sarker *et al.* (2012) used ordinary least squares (OLS) and median (quantile) regression methods to explore the relationship between climate change and rice yield in Bangladesh. They used time series data for the period 1972-2009 at the aggregate level, and their findings confirm that climatic variables have had significant effects on rice yields; this poses threats to the food security of Bangladesh since rice is the staple food crop. However, Chowdhury and Khan (2015) experienced some problems associated with the use of the linear regression model, and rather decided to further the study using a multiple linear regression model. Their results, however, reveal that maximum temperature is statistically significant and negatively affects the yield of rice. These studies, however, focused only on rice yield, therefore there a need to focus on other cereals crops such as maize, which is the principal provider of calories.

Furthermore, Amikuzino and Donkoh (2012) identified this gap in the literature and carried out a study on climate change and yields of major staple food crops in Northern Ghana. They applied pooled panel data of rainfall, temperature and yields of selected crops for the period 1976-2010. Granger causality and cointegration models were used, and their results show that there is convincing evidence of cointegration between total seasonal rainfall and crop yields, and there is causality from rainfall to crop yields in Northern Ghana. The temperature was, however, found to be reasonably stable over the period of the study, and it was therefore left out of their impact analysis. Using the same methodology, Igwe *et al.* (2013) analysed the direction of causality and effect of climate change on food grain output in Nigeria using time series data for the period 1970-2010. Results from the pairwise regressions suggest that changes (decrease in rainfall and increase in temperature) in climatic parameters positively affect foodgrain yield in Nigeria. However, this might not be the same in all countries and regions. The environmental footprint of agricultural production can vary significantly between countries and within a country based on regional conditions and agricultural practices (Pryor *et al.*, 2017). Thus, carrying out research analysing the linkages between climate variables and maize production in South Africa is necessary.

Owusu and Asumadu-Sarkodie (2016) extended the study in Ghana, and analysed the causal effect of agricultural production and carbon dioxide emissions. They used time series data spanning from 1960 to 2015, and analysed it using the Auto-Regressive Distributed Lag (ARDL) model. Their results indicate that there was a long run equilibrium relationship running from corn production, millet production and sorghum production to carbon dioxide emissions. There was a bidirectional causality between millet production and carbon emissions, and a unidirectional causality from corn production to carbon dioxide emissions. Boansi (2017) also used an ARDL modelling approach and pair wise Granger causality tests to investigate the effect of climatic factors on cassava yields in Togo. A unidirectional relationship between main-season rainfall and lean-season mean temperature to cassava yields thus supports the view of Amikuzino and Donkoh that seasonal rainfall influence crop yields, but this was only for cassava production and did not include other crops.

Severe droughts are likely to become more frequent in Southern Africa, South-East Asia, the Mediterranean and Central Asia, which will lead to a decline in agricultural productivity by 20% (Edame *et al.*, 2011). In Nepal, Poudel and Shaw (2016) conducted a study that focused on the relationship between climate variability and crop yield using correlation coefficient and multivariate regression analyses with the help of SPSS. The regression analyses revealed negative relationships between maize yield and summer precipitation and between wheat yield and winter minimum temperature. Because South Africa is one of the countries in southern Africa that was highlighted to be most affected by severe droughts, it is necessary to study the linkages between climatic variables and cereals production so that sustainable mitigation of climate change can be attained, as well as sustainable reduction of food insecurity.

Celikkol and Guven (2017) employed the Error Correction Model (VECM) to uncover causalities between agriculture and climate change. They used back-dated actual panel data extracted from 145 countries over a nine-year period from 2002 to 2010. The study captured economic and agricultural activities, as well as agricultural emissions from these activities, and noted temperature anomalies in this causal relationship. Their study suggests that there is a statistically significant long-run causality among the variables in question, and it is a unidirectional causality that occurs from temperature anomalies, squared GDP per capita, and agricultural share to agricultural emissions resulting from nitrogen fertiliser. Although the results from this study highlighted that agricultural emissions from the use of nitrogen fertilisers do not cause temperature anomalies, it does not mean that there are no feedback loops from agricultural emissions (Celikkol and Guven, 2017). There is therefore need for a study that will assess the linkages between agriculture and climate change in South Africa.

In conclusion, several studies have been carried out to determine the direction of causality between climatic variables and crop production using methodologies which include VECM, Granger causality, correlation coefficient and ARDL using simple linear regression models in different countries. However, studies like this are still very limited in South Africa, and consequently the objective of my study is to analyse the causalities between climatic variables and crop production using the Granger causality analysis as it was used by Igwe *et al.* (2013) in Nigeria, as previously mentioned.

2.5 Overview of the physio-economic impacts of climate change on agriculture

The ongoing changes in climate have significant impact on agricultural production (De Salvo *et al.,* 2013). Both crop production and livestock production are at risk. The losses in productivity will therefore potentially lead to other costs, such as losses in profitability and fewer employment opportunities, thus threatening food security. Several studies have analysed the impact of climate change on crop production. Examples include Mendelsohn *et al.* (1994); Isik and Devadoss (2006); Deressa and Hassan (2009); Maharjan and Joshi (2013); Wing and Fisher-Vanden (2013); Nhemachena *et al.* (2014); Stanton *et al.* (2015); and Wiebe *et al.* (2015) among others. The majority of their findings suggest that climate change has serious consequences for the agricultural sector. Moreover, this implicates the whole economy since agriculture has many forward and backward linkages to other sectors of the economy.

2.5.1 Effects of climate change on crop production

As an economic activity, agriculture is particularly dependent upon weather and climate to produce food and feed to sustain lives. Agriculture is therefore deemed to be vulnerable to climate change in many parts of the world because it involves natural processes that often need fixed proportions of nutrients, rainfall, temperature and other weather conditions (Yohannes, 2016). Agriculture is known to contribute 2.9% to the world overall; however, it contributes more to developing countries, especially in Africa. For instance, it contributes about 43% to the GDP of Ethiopia (International Monetary Fund, 2012). In the case of South Africa, the agricultural sector contributes less to the GDP, but it continues to play an important role in the economy (Hlomendlini, 2016). The sector also ranks high regarding its backward linkages with the manufacturing sector, and acts as a major labour-intensive employer in the economy of South Africa. It means, therefore, that any influences (for example, by climate variability and change) on agriculture have a significant impact on a large number of households and the greater economy owing to its influence on employment and food security.

Yohannes (2016) identified that change in climate influences agriculture in a number of ways. For example, climate change affects agriculture through variations in the average temperatures;

rainfall and climate extremes have an essential impact on soil erosion (for example, floods and drought); pests and disease proliferation; changes in atmospheric carbon dioxide; nutritional quality changes in some foods; shifting of the growing seasons; and changes in the sea level. Hoffmann (2013) suggests that crop yields display a significant correlation with temperature changes and with the duration of heat or cold waves, and yields fluctuate based on plant maturity stages during extreme weather events. Changes in the rainfall patterns heighten water scarcity, which in turn alters irrigation water, leading to drought stress for crops whose growth mainly depends on water, such as maize. These changes in rainfall patterns also pose a severe challenge for farmers as it will make it difficult for them to predict when they are planning (OECD, 2014). The changes in temperature and moisture levels will have an indirect influence as they affect the absorption rate of fertilizers and other minerals that determine the crop yield. In a nutshell, the combined effect of a rise in temperature and a decrease in the amount of rainfall received per area will lead to a reduction of the agricultural productivity, provided these changes are beyond the threshold that is suitable for crop production. Climate change is therefore seen to be responsible for the reduction in the output of field crops, and these are predicted to fall seriously globally by 2050.

It is, however, essential to know that the impacts of climate change are substantial and variable according to regions. Some regions are seen to be benefiting from a changing climate, whereas others are adversely affected. In the case of crop productivity, it is projected to have a slight increase in the mid- to high-latitude areas (Yohannes, 2016). In contrast, crop productivity is projected to fall in the lower-latitude areas, especially seasonally dry and tropical regions given a slight increase in the local temperature, thus stimulating the risk of food shortages as a result of diminished yields (OECD, 2015). In view of this situation, countries of sub-Saharan Africa are therefore at great risk of an increase in warming because millions of people in this region rely on agriculture (IPCC, 2015).

Lobell *et al.* (2008) studied 12 food insecure regions of the world, and their research suggests that climate change may impact on agricultural crop production up to 2030. In particular, sub-Saharan Africa and South Asia will be the most influenced owing to increased variability associated with both temperature and rainfall. Okoloye *et al.* (2013) supported this idea when they carried out a study in Nigeria. Their study shows that in recent years, the climatic variables have changed enormously, resulting in a high frequency of drought and floods. Similarly, in support of the same idea, Guiteras (2009) suggests that climate change will impose significant costs on the Indian economy by altering major crop yields.

Maize is identified as the most widely-grown crop in the world, and it is the number one largest calorie source, therefore it plays a significant role in livelihoods (Lobell *et al.*, 2008; Schlenker *et al.*, 2013). However, as with any other field crop that depends mainly on water for its growth, maize production is influenced by climate change because the weather is an essential input into its production (Howden *et al.*, 2007; Fisher *et al.*, 2012). There is mounting evidence, notably from statistical yield models that estimate the climate-yield relationship from historical data, that climate change is transforming maize yields negatively in the major producing regions (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Fisher *et al.*, 2012; Ortiz-Bobea and Just, 2013; Burke *et al.*, 2015; Chen *et al.*, 2015). However, evidence regarding the impact of rising temperatures on maize yields still relies heavily on process-based approaches (Asseng *et al.*, 2015). The majority of these conclusions were arrived at using different approaches to measure the impact of climate change on agriculture. However, there are many disagreements in terms of models that were used by these studies to measure the impact of climate change on agriculture. The following section discusses the different types of approaches used in the estimation of the impact of climate change on agriculture.

2.5.2 Approaches to measure impacts of climate change on agriculture

The approaches used to estimate the impact of climate change on agriculture are outlined starting with the structural approaches, followed by the spatial analogue approaches, integrated assessment approach, and the production function approach. An outline of how these approaches operate, as well as their respective advantages and disadvantages, is discussed under this section.

Structural approaches

The issue of the impact of climate change has been addressed using different types of tools, as stated previously. Each of these tools takes a specific angle, and generates an answer based on the chosen methodology. These different tools can be combined into a structural approach using the links between models and data (Reilly and Willenbockel, 2010). The structural approach is therefore seen to have three major components, namely physiological models, crop models and economic models. The physiological models estimate how climatic variables (temperature and rainfall) and other factors affect crops. Crop models simulate how yields change using either historical data or future projections, whilst economic models estimate how yields will change when market interactions are considered. The influence of climatic elements in all the three components is based on the general circulation model (GCM) results. IPCC (2013) defined GCMs as numerical models that represent physical processes in the atmosphere, ocean, cryosphere and land surface when simulating the response of the global climate system to increasing greenhouse gas concentrations.

There are some advantages and disadvantages associated with the use of structural approaches. One of the advantages is that structural approaches allow a detailed understanding of the biophysical responses coupled with the adjustments that can be made by farmers in response to changes in climate (Adams, 1999). Additionally, through the use of economic models, structural approaches are beneficial since the economic models enable the identification of gainers and losers from climate change (Nhemachena *et al.*, 2014). However, structural models have a disadvantage in that adaptations that are included in the agronomic models do not consider some economic factors or limitations in human capital that influence farming decisions (Mendelsohn and Dinar, 1999). Moreover, because action is often based on results from a small number of laboratories and experimental sites, the use of structural models might be problematic. Furthermore, structural models are associated with exorbitant costs, thus making it difficult to use them in developing countries (Adams, 1999; Mendelsohn and Dinar, 2009; Nhemachena *et al.*, 2014).

Spatial analogue approaches

Spatial analogues are the regions today that have a climate analogous to that predicted in the study region in the future (Flechard *et al.*, 2007). These approaches make use of cross-sectional evidence and statistical estimations to model the effects of climate change on agricultural production in different regions. The approaches include the evidence of farmers' adaptation practises to changes in climate, as well as other farmer management practises. Furthermore, the spatial analogue approaches allow for the use of other factors that influence crop production, including soil type and soil quality, thereby making the estimation more reliable for interpretation. This feature of including factors like soil type and soil quality makes spatial analogue approaches better when compared to structural approaches (Adams *et al.*, 1998).

The spatial analogue approaches are mainly associated with methods such as the Ricardian approach by Mendelsohn *et al.* (1994) and the Future Agricultural Resources Model (FARM) by Darwin (1999). FARM models estimate the potential impact of climate on agriculture and other sectors in different regions. FARM models make use of computable general equilibrium models (GEM), and estimate economic changes and effects on agricultural production and prices (Adams *et al.*, 1998). The Ricardian approach, on the other hand ,measures the value of land using economic data, as well as some climatic variables (Mendelsohn *et al.*, 1994). The estimation of the effects of climate on value of farmland in different places is supported by this model. The benefit of using the Ricardian approach is that it automatically incorporates efficient adaptations by farmers to climate change (Mikemina, 2013). It also incorporates the substitution of different inputs and other farming techniques that the farmers have adopted, given the prevailing climate (Kurukulasuriya *et al.*, 2006). The approach also allows the use of time series data at national level and the use of a single crop, therefore it is cost effective. Given this advantage, the Ricardian model is adopted in this study using secondary data at national level. However, as with any other model, the Ricardian approach can be criticised. For instance, it fails to fully take into account the impact of important factors that can also explain farm incomes (Mikemina, 2013). Although having some limitations, Mendelsohn and Dinar (1999) argue that the problems are not serious.

Integrated assessment models

Literature has used integrated assessment models (IAMs) to analyse the impact of climate change (Strzepek *et al.*, 2013; Tai *et al.*, 2014). Nhemachena *et al.* (2014) highlighted that IAMs predict a range of changes to the climate from GHG emissions to final impacts on the economy. Wing and Fisher-Vanden (2013) further elaborated on this notion, and draw a diagram that shows a bottom-up framework of how climate change leads to economic impacts. As outlined by their framework, the IAMs include the following components: factors that determine socio-economic development, emissions caused by economic growth, the atmosphere-ocean-climate system, ecosystems, socio-economic impacts, mitigation and adaptation policies and associated economic responses, with different models explaining different associations. However, estimations of IAMs is mainly based on projected climate changes and climate sensitivity, which is problematic since it might lead to spurious accuracy owing to the overly-elaborated economic models (Nhemachena *et al.*, 2014; Stanton *et al.*, 2015).

The production function approach

The production function approach is based on an empirical or experimental production function that measures the relationship between agricultural production and climate (Deressa, 2007). The model used in this case includes climatic variables as inputs to production. The estimates of the influence of climatic variables in the production function are measured and analysed at testing sites and are aggregated to reflect the national situation. The model on its own predicts the manner in which climate change affects yield because of the controlled experiments. However, the production function approach fails to account for adjustments by farmers; consequently, the spatial analogue's Ricardian model seems to be the best approach to model the impacts of climate change on agricultural production (Mendelsohn *et al.*, 1994).

2.6 Conclusion

The literature shows that there are different conclusions about the relationship between agricultural production and the changes in climate. Many of these differences are explained by variations in weather conditions in different regions around the globe. Although there are different assumptions about the linkages between agriculture and climate change, the evidence provided by literature is enough to show that agricultural production has become a threat to the climate, which will in turn negatively affect the same agricultural production. Evidence of the significant impacts of climate change on agriculture has been alluded to by literature (Eastin *et al.*, 2011; Nhemachena *et al.*, 2014). Considering the different methodologies used in literature, this study adopts the Granger causality analysis to analyse the first objective and the Ricardian model to analyse the second objective given their advantages. For instance, to determine whether the interaction between two time series is direct or mediated by another recorded time series, Granger causality gives a better analysis (Gujarati, 2004). Also, the Ricardian model is considered for the estimation of impacts of climate change since it considers adaptation as compared to other methodologies like the production function model which do not consider it.

Chapter 3
A time series analysis of the causality between climate change and maize production in South Africa

3.1 Introduction

There has been evidence of global warming since 1901, but most of the warming was recorded from the 1970s onwards after several anthropogenic forces occurred, including the agricultural green revolution of the 1960s. Valin *et al.* (2013) indicated that warming has taken place since the 1980s, with much of it becoming evident at the beginning of the 21st century. In 2016, the World Economic Forum also supported the view that the climate is warming, and highlighted that the globe has experienced an increase in warming with a minimum of 2°C since the beginning of the 1900s. Much of this warming can be attributed to rapid developments in all sectors of the economy, with manufacturing and agriculture being in the lead (Scholtz *et al.*, 2014).

Agricultural activities such as land clearing increased dependency on agro-chemicals for both crop and animal production (e.g., chemical fertilizer, herbicides, insecticides, vaccines and antibiotics, and biotechnology, among others), and stimulate the rate at which the climate is changing (Adomako and Ampadu, 2015). This is because such activities disturb the self-regulatory state of the earth by saturating the atmosphere with different greenhouse gases (Lenton and Latour, 2018).

According to Lal (2004), agricultural emissions are in three forms: Nitrous oxide (N_2O), Methane (CH_4) and Carbon dioxide (CO_2). Agricultural CO_2 emission mainly come from agricultural processing, the use of agricultural machinery (like tractors and combine harvesters) that burn fossil fuels, and from conventional tillage, which causes soil compaction and removes the CO_2 stored in the soil (Lal, 2004; Pryor *et al.*, 2017). Emissions of N_2O are mainly attributed to crop production and farm activities that lead to its emissions, including the use of synthetic fertilizers, pesticides and other agricultural chemicals. N_2O emissions can also be caused by industrial activities such as fertilizer and seed production, which affect maize production indirectly. In addition, CH_4 emission comes from livestock farming, landfills and waste, fossil fuel use, biomass burning, and irrigation crop production. Amongst the three greenhouse gases, it has been established that CO_2 stays in the atmosphere for centuries in comparison with the other two (CH_4 and N_2O). However, Lanigan (2017) highlighted that CH_4 and N_2O absorb more ultraviolet radiation compared to CO_2, therefore they are more dangerous. As a result, it is a concern as these two greenhouse gases (CH_4 and N_2O) are mainly emitted by livestock and crop production.

In South Africa, maize is the dominant crop produced and it contributes a significant percentage of agricultural emissions in the country (Tongwane *et al.*, 2016). Fao.org (2018) identified South Africa as one of the major producers of maize in the world and as the largest producer in the SADC region, producing above 10 million metric tons annually, averaging 4.2 metric tons per hectare. In addition, the maize industry in South Africa is one of the largest, producing between 25% and 33% of the average gross agricultural production of R2.7 million. Given the intensity of South Africa's maize production, it is therefore regarded as the largest emitter of agricultural emissions in the region (Opara, 2013). An atmosphere saturated with greenhouse gases experiences serious climate warming, which has some serious consequences for the production of maize in the country.

Warmer temperatures have an impact on plant growth, especially during the reproductive stage of maize crops (Du Plessis, 2003; Hatfield and Prueger, 2015). The impact of high temperatures on plant growth is also seen in the increased water deficit. South Africa is a water scarce country, therefore increased climate warming will inevitably have a negative impact on maize production (Müller *et al.*, 2011). A downward shift in the maize production levels will, therefore, spell some serious economic problems given the importance of the maize crop in the country. Some of these economic problems include price increases of maize by-products (for example, maize meal and samp), rising unemployment rates as farm workers may lose their jobs; reduced agricultural exports and increased imports, worsening the country's balance of payments, as well as food insecurity problems (Parihar *et al.*, 2016). Consequently, maize production activities can lead to climate change that in its turn impedes crop growth.

The effects of climate change can be worsened when trying to limit some of the above-mentioned economic problems. For instance, increasing crop production to attain the country's state of food self-sufficiency may increase agricultural emissions, thus exacerbating climate change. The population of South Africa is growing at a rate of 1.55% per year and is estimated to be around 68 642 000 people by 2050, growing from 57 725 600 people in 2018 (STATS SA, 2018). Farmers in South Africa are therefore obliged to scale up their production to meet the rising food demand, especially for maize, which is a staple crop. The increase of maize production entails more usage of fertilizers, agricultural chemicals and agricultural machinery, therefore more greenhouse gases can be emitted, thus increasing the rate at which the climate is changing.

This study therefore aims at identifying the causal relationship between maize production and climate change. This will enable policy makers and farmers to give more attention to sustainable maize farming practises. A previous study by Ziervogel *et al.* (2014) investigated the mitigation strategies and the adaptation strategies towards climate change. However, they failed to account for the causality between climatic variables and maize production, which is an important relationship to consider in a discourse about mitigating sustainable climate change.

3.2 Conceptual framework

The conceptual framework for this study was adopted from Wang and Huang (2005), with some adjustments to suit this study. Climate change is always linked to crop production, and there are some feedback loops between the two. Crop production mainly involves activities that result in emissions of methane, nitrous oxide and carbon dioxide. This includes, for example, the application of synthetic fertilizers, the use of agricultural chemicals, as well as the use of agricultural machinery (Lipper *et al.*, 2014; Pryor *et al.*, 2017). The increased agricultural emissions lead to an increased concentration of greenhouse gas emissions into the atmosphere, which attracts ultraviolet B radiation from the sunlight, thus adding to the influence of natural forces on regional climate change. According to literature, crop production mainly depends on the climatic elements (rainfall and temperature), therefore a change in the climate results in some fluctuations in the crop yields (Hoffmann, 2013; Yohannes, 2016). Because the changes in crop yields have a significant impact on socio-economic outcomes (food security, employment, total revenues and agricultural exports, for instance) policymakers and farmers devise a number of strategies of adaptation that stimulate crop production and yields.

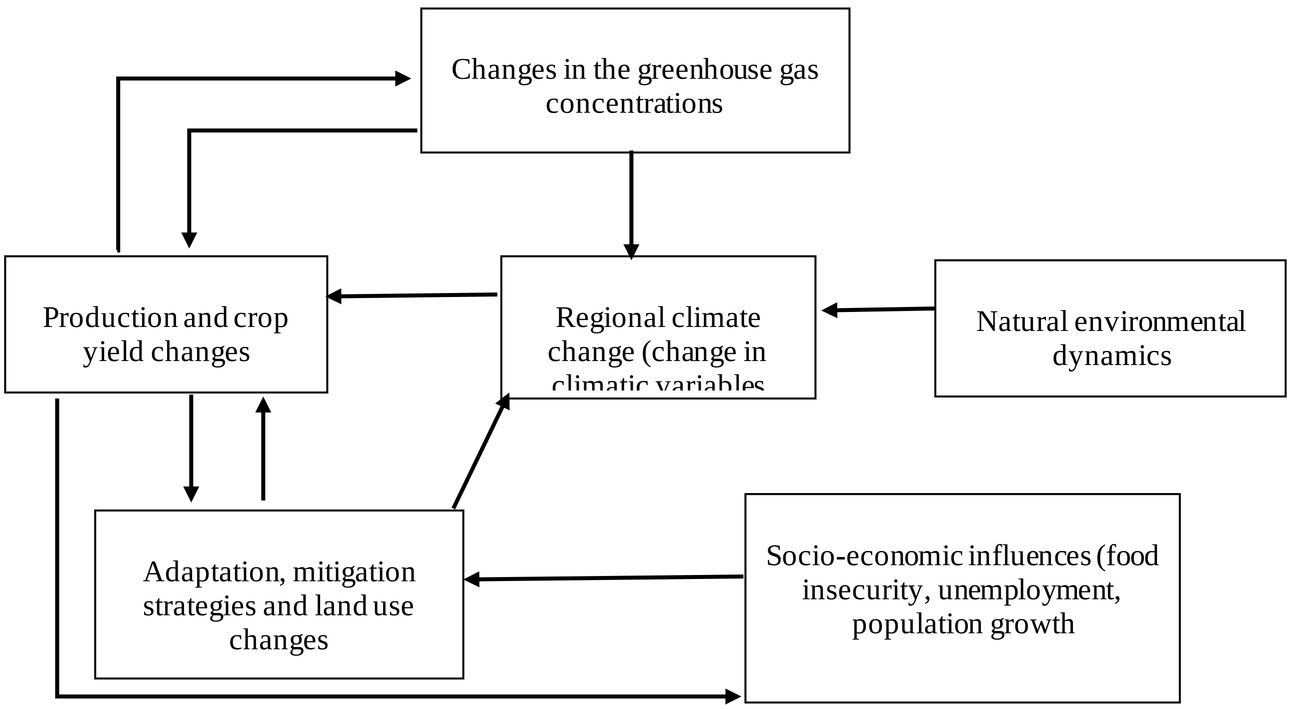


Figure 3.1: Conceptual framework for climate change and agricultural production

Source: *Author's construction*

As depicted in Figure 3.1, production and crop yields are influenced by changes in greenhouse gas concentrations, changes in climatic variables, changes in land use, and adaptation strategies. However, production tends to have a reverse impact on the concentration of greenhouse gases in the atmosphere, and together with the natural environmental dynamics, this will increase regional climate change. The changes in the regional climate have some implications for crop production and yields. Thus, some implications on the socio-economic characteristics can be realized. Given the effects on the socio-economic characteristics, adaptation and mitigation strategies are then put in place to cope climate change and stimulate maize production.

3.3 Research method

3.3.1 Study area

The study was conducted in South Africa, which is on the southernmost part of Africa and shares borders with Botswana, Zimbabwe, Namibia, Swaziland, Mozambique and Lesotho. South Africa has a semi-arid climate that is shaped by its plateau topography, sub-tropical latitude, and the Agulhas and Benguela ocean currents. The country has low-level zonal circulations that change seasonally, and rainfall variability is influenced by the Pacific El Niño southern oscillation (ENSO) and adjacent South Atlantic and Indian Ocean sea surface temperatures. Apart from the natural forces, climatic elements are also influenced by the moisture that is internally recycled via surface fluxes and local overturning circulations (Chikoore and Jury, 2010).

The maize producing areas in South Africa consist of Mpumalanga, Free State, North West, Limpopo and KwaZulu-Natal provinces as shown in Figure 3.2. Climatologists characterize the maize rain-fed cropping areas into four major regions, namely the warm eastern region, temperate eastern region, cold eastern region and the KwaZulu-Natal region. The rainfall in these regions is relatively erratic, averaging between 550mm-650mm in the western part and 650mm-850mm in central and eastern parts. The other areas mainly practice irrigation farming, and therefore maize production is undertaken in all provinces of the country, although Mpumalanga, Free State and North West are the leading production areas.

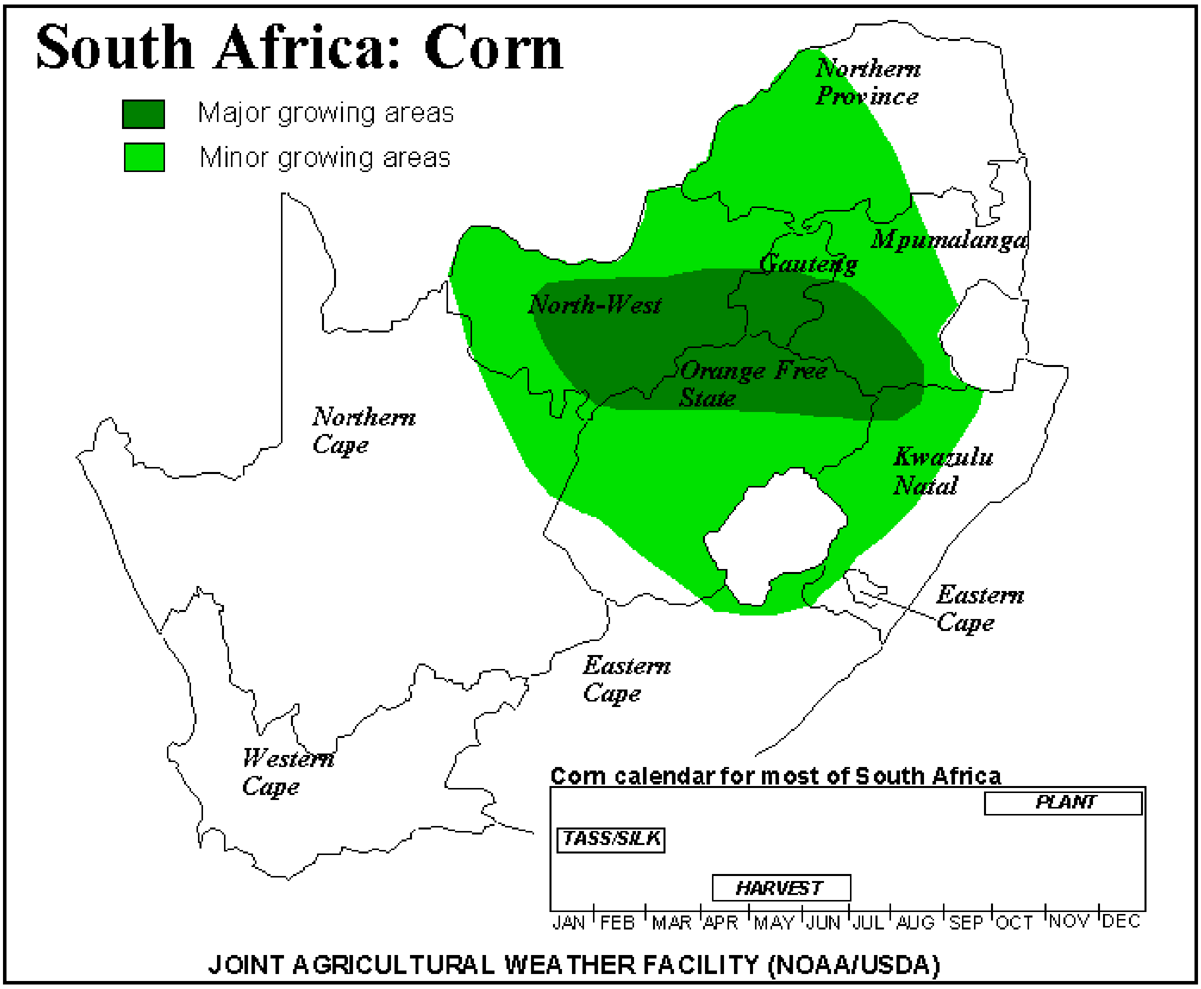


Figure 3.2: Map of South Africa showing the maize growing area

Source: *Jordan et al. (2015)*

3.3.2 Data sources and type

All the data were obtained from secondary sources published by the World Bank, Department of Agriculture, Forestry and Fisheries (DAFF), and the South African Weather Services (SAWS). The time series data used in this study was annual for all the variables which are temperature (TMP), rainfall (RFLL) and maize production (MPX) covering the period 1911 to the end of 2016. A long study period was chosen since time series analysis requires a large sample of observations to produce more reliable estimates. All the data were collected at national level owing to shortages of data at a small scale. The descriptive statistics for the data used are presented in Table 3.1.

Table 3.1: Descriptive statistics of variables

	MPX	RFLL	TMP
Mean	5424.862	39.25644	17.57899
Median	4283.500	38.74270	17.56440
Maximum	14656.00	56.52372	18.71144
Minimum	757.0000	26.03139	16.42110
Std. Dev.	3868.918	6.336905	0.534038
Skewness	0.510684	0.408201	0.084918
Kurtosis	2.010421	2.800315	2.437662
Jarque-Bera	8.932518	3.119869	1.524052
Probability	0.011490	0.210150	0.466720
Sum	575035.4	4161.183	1863.373
Sum Sq. Dev.	1.57E+09	4216.419	29.94569
Observations	106	106	106

As shown by the descriptive statistics in Table 3.1, rainfall (RFLL) and temperature (TMP) have lower standards deviations, which suggests less impact of outliers on the empirical estimates in this study. Maize production (MPX) has a relatively higher standard deviation, but it does not differ much from the mean of (MPX), therefore outliers may not have a significant impact on the production. The probability values of the Jarque-Bera statistics show that the series is normally distributed, thus suggesting more reliable estimations for this study.

3.3.3 Analytical/estimation framework

The Granger analysis was used to analyze the linkages between maize production and climatic elements (rainfall and temperature) for the period 1911 to 2016. The Granger causality test can be done in two ways, that is by running Pair wise causality analysis (known as the F-test), or by running a VAR Granger analysis (Gujarati, 2004). Toda and Yamamoto (1995) argue that the F-test of the traditional Granger causality may be invalid in the presence of integrated or cointegrated time series data because it has no standard distribution. Given that climate change is a dynamic process and its effects are realized after a longer period (Savitsky, 2017), the F-test of the traditional Granger may fail to produce proper estimation. As a result, VAR Granger analysis (Block Exogeneity Wald test) was therefore considered as the best to run causality tests between climatic elements and maize production in this study because it captures the dynamic causalities between the variables in the VAR system. The empirical model estimated in this study is therefore as follows.

Empirical specification of the VAR Granger model:

$$MPX_t = \sum_{t-n}^{n} \alpha_1 C_{t-n} + \sum_{t-n}^{n} \beta_1 MPX_{t-n} + \mu_{1t} \quad (3.1)$$

$$C_t = \sum_{t-n}^{n} \beta_1 MPX_{t-n} + \sum_{t-n}^{n} \alpha_1 C_{t-n} + \mu_{2t} \quad (3.2)$$

where C_t *is the vector of climatic elements (rainfall and temperature) at time* t*;* MPX_t *is the maize production at time t; t-n represents number of lags;* α_1 *and* β_1 *are parameters to be estimated;* μ_{1t} *and* μ_{2t} *are the error terms from the estimation.*

First, the causality analysis was carried out between climatic variables (temperature and rainfall) and maize production. The test investigated whether temperature and rainfall are Granger causal (have an influence) on the current production of maize. Secondly, the test was done also to investigate if the past production of maize is Granger causal to the climatic variables (temperature and rainfall). The Granger causality tests were carried out using the Wald block endogeneity tests following the Toda and Yamamoto procedure (Toda and Yamamoto, 1995). Using equations (3.1) and (3.2), the causalities between climatic elements (rainfall and temperature) and maize production were investigated, and the following outcomes were investigated.

1. Unidirectional causality from climatic variables (temperature and rainfall) to maize production. In this case temperature or rainfall influence maize output, but not vice versa.

2. Unidirectional causality from maize production to variations in temperature and rainfall. This means maize production has an influence on the variations in temperature or rainfall, and not vice versa.

3. Bidirectional (or feedback) causality. In this case, climatic variables (temperature and rainfall) are Granger causal to maize production, and vice versa.

4. Independence between climatic variables (temperature and rainfall) and maize production. In this case, there is no causal relationship between climatic variables and maize output.

The only disadvantage of causality analysis is that it does not necessarily imply that climatic variables vary as a direct consequence of changes in maize production or vice versa, but rather that there is a clear chronological ordering of movements in the series (Igwe *et al.*, 2013). Moreover, on the other hand, persistence in this chronological ordering, in the long run, becomes worrisome as it tends to be a clear causality between the climatic variables and maize production (Amikuzino and Donkor, 2012). It is therefore important to determine if there is a short run or long run relationship between climatic elements and maize production. The short run or long run relationship was therefore analyzed using the variance decomposition from the VAR system.

Variance decomposition is a breakdown of the forecast error variance (FEVD) for a specified period. The FEVD was used to estimate both short run and the long run relationship between variables in the system (temperature, rainfall and maize production) (Obasaju and Baiyegunhi, 2019). The estimation of the FEVD can be stated as follows:

$$MPX_t - \overline{MPX} = \sum_{i=1}^{\infty} \varphi_{11} \varepsilon_{MPX_{t-i}} + \sum \varphi_{12} \varepsilon_{C_{t-i}} \quad (3.3)$$

$$C_t - \overline{C} = \sum_{i=1}^{\infty} \varphi_{21} \varepsilon_{MPX_{t-i}} + \sum_{i=1}^{\infty} \varphi_{22} \varepsilon_{C_{t-i}} \quad (3.4)$$

Equations (3.3) and (3.4) above clearly show that deviations in maize production (MPX_t) and climatic elements (C_t) occur because of shocks in the error terms denoted by ($\varepsilon_{MPX_{t-i}}$) and ($\varepsilon_{C_{t-i}}$). It is, therefore, equations (3.3) and (3.4) that determine the short run or long run relationship between maize production and climatic elements in this study.

3.3.4 Time series properties and the diagnostic tests of the VAR Granger model

Before running the VAR Granger analysis and variance decomposition, it was important to carry out some diagnostic checks to ensure that reliable results were produced. As a result, the stationarity test of the time series data was done to ensure that there are no unit roots that invalidate many standard empirical results (Kwiatkowski *et al.*, 1992). Stationarity tests were done using both the augmented Dickey-Fuller test and the Phillips-Perron test, and decisions were made guided by 1% and 5% levels of significance. The series that were not stationary were differenced to remove the unit roots in the series and ensure stationarity.

In the case of a number of lags, Gujarati (2004) stated that too many lags might lead to multicollinearity, whilst too few lags will lead to specification errors. The optimal lag length can be determined by several criteria, which include final prediction error (FPE), Akaike Information Criterion (AIC), and the sequential modified (LR) test, among others. In this instance, all criterions were considered then a smallest lag length was selected from them (Belloumi, 2009).

It was also important to ensure that the VAR system was stable because an unstable system could result in an unreliable interpretation of results from the VAR system (Lütkepohl, 2007; Lütkepohl, 2018). The inverse roots of the auto-regressive characteristic polynomial test were used to determine if the VAR system is stable. Having all the roots less than 1 in absolute terms was a favourable result as this entails a stable VAR system than has roots greater than 1. Other diagnostic tests (autocorrelation, heteroskedasticity and normality) were also carried out to ensure reliable estimations, and these are presented as appendices to this study.

3.4 Unit root test of variables

As shown in Table 3.2, the Augmented Dickey-Fuller (ADF) suggest that maize production (MPX) contains a unit root and becomes stationary after first difference (integrated of order one I(1)). However, the Phillips-Perron (PP) test results suggest that MPX is stationary at level showing the absence of a unit root in the series. Given the contradicting results from the two tests, the study used the Phillips–Perron test since it makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation unlike the Augmented Dickey-Fuller test. As temperature (TMP) and rainfall (RFLL) both the tests (ADF and PP) comply and suggest the absence of unit roots, meaning they are stationary at levels (integrated of order zero I(0)). The decisions to accept or reject the null hypotheses were made guided by the probability values (p-value) where p-values less than 0.05 led to the rejection of the null hypotheses, which were stating that there is a unit root in the series.

Table 3.2: Stationarity test results

Variables	Test in	ADF		PP	
		t-stat	p-value	t-stat	p-value
MPX	Level	-0.963	0.7639	-3.001	0.0380**
	1st difference	-10.705	0.0000***	N/A	N/A
TMP	Level	-3.709	0.0053***	-3.316	0.0166**
	1st difference	N/A	N/A	N/A	N/A
RFLL	Level	-9.687	0.0000***	-9.688	0.0000***
	1st difference	N/A	N/A	N/A	N/A

where MPX, TMP, and RFLL represents South Africa maize production, temperature and rainfall respectively. *** *and ** denotes significance at 1% and 5% respectively.*

According to literature, in cases where there are no two or more series containing unit roots, there is no reason for running cointegration (Sims *et al.*, 1990; Toda and Yamamoto, 1995; Ashley and Verbrugge, 2009); therefore, a structural VAR model can be used to assess the relationships between climatic variables and maize production.

3.5 Lag selection criteria

Given all the lag order selection criteria, the smallest lag length detected was the optimal lag length in this study. The results from this study suggest 1 as the optimal number of lags for the system as selected by the BIC criteria. The results for lag order selection criteria are shown in Table 3.3.

Table 3.3: VAR Optimal lag selection

Lags	LogLik	p(LR)	FPE	AIC	BIC	HQC
0	-1335.929	NA	85578178	26.77857	26.85673	26.81020
1	-1245.915	172.8250	16933530	25.15831	25.47093*	25.28483
2	-1231.832	26.19551	15305059	25.05664	25.60372	25.27805*
3	-1219.036	23.03239	14204973	24.98072	25.76227	25.29703
4	-1209.546	16.51329	14100512	24.97091	25.98693	25.38211
5	-1192.116	29.28204*	11959148*	24.80232*	26.05280	25.30841
6	-1183.705	13.62604	12170033	24.81410	26.29904	25.41508

VAR system, maximum lag order 6. (*) indicates the best values of the respective information criterion, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion

3.6 Model diagnostic tests

Before estimating the VAR Granger causality model, it is important to conduct some preliminary tests to ensure the reliability of the model. These preliminary tests are presented as appendices to this study. The results of the model stability test guided by the inverse roots of the auto-regressive characteristic polynomial suggest that the model is stable because all the roots are less than the modulus of one in absolute terms; thus the results from the system are reliable for interpretation.

Many time series analyses are believed to have the problem of autocorrelation (Gujarati, 2004). As a result, the residual serial correlation Lagrange Multiplier (LM) test was run to ensure the absence of autocorrelation in the VAR model. The probability values of the LM statistics were found to be above the 5% level at all lags, accordingly there is no problem of autocorrelation in the model.

The normality test of the model was also done using the Cholesky residual normality test of Lütkepohl. As suggested by Lütkepohl (2007), it is recommended to use the skewness and kurtosis of standardized residuals in case of multivariate analysis. The normality test results, therefore, suggest that the null hypothesis of normality cannot be rejected, therefore making the model reliable for interpretation. Although the joint statistics of Kurtosis is highlighted that the problem of normality might exist, Lütkepohl (2018) noted that non-normality is not an issue of concern in terms of statistical procedures related to VAR models, thus the model remains reliable for interpretation.

The problem of heteroskedasticity was also absent in the model as the p-value of the chi-square (chi-sq) statistic (as presented in Appendix A 4) is greater than the 5% level. This ensures that estimations of the VAR Granger model are reliable for interpretation.

3.7 Estimation results

3.7.1 VAR Granger causality test results

The results from the VAR Granger Wald tests show that the null hypothesis (rainfall does not Granger cause maize production can be accepted since the probability value (0.1409) is greater than all the significance levels (1%, 5% and 10%), as shown in Table 3.4. A combination of temperature (TMP) and rainfall (RFLL) is however granger causal to maize production (MPX) since their joint probability (0.0001) is less than all the significant levels. There is also a bidirectional causality between TMP (p-value=0.0000) and MPX (p-value=0.0001). Maize production is significantly Granger causal to temperature at 1% level of significance and on the other hand temperature is significantly Granger causal to maize production at 1%. These Granger causality results are presented in Table 3.4.

Table 3.4: VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: MPX			
Excluded	**Chi-sq**	**Df**	**Prob.**
RFLL	2.168394	1	0.1409
TMP	18.26827	1	0.0000***
All	18.78208	2	0.0001***
Dependent variable: RFLL			
Excluded	**Chi-sq**	**Df**	**Prob.**
MPX	0.000667	1	0.9794
TMP	0.097087	1	0.7554
All	0.152813	2	0.9264
Dependent variable: TMP			
Excluded	**Chi-sq**	**Df**	**Prob.**
MPX	14.63184	1	0.0001***
RFLL	1.198818	1	0.2736
All	14.80573	2	0.0006***

where *** represents significance at 1%

3.7.2 The forecast error variance decomposition results

The results suggest that shocks in maize production itself have more significant impact on maize production right from the short run (1^{st} year) to the long run (15^{th} year). The same result holds for both rainfall and temperature variance decompositions, which are presented as Appendix A and B respectively. Although with smaller magnitudes, the effects of climatic variables are realized in the long run (from year 3 for rainfall and from year 2 for temperature). A relatively larger impact (above 10% magnitude of impact) was realised for temperature on maize production starting from the 3^{th} year whereas for rainfall it remained relatively low in the forecast. The results for the forecast error variance decomposition of maize production are shown in Table 3.5.

Table 3.5: Variance decomposition

Variance decomposition of MPX:				
Year	**S.E**	**MPX**	**RFLL**	**TMP**
1	2090.394	100.0000	0.000000	0.000000
2	2552.395	92.85203	0.005432	7.142536
3	2847.826	85.59755	1.028805	13.37365
4	3068.937	80.28792	2.115671	17.59641
5	3238.301	76.65916	2.933570	20.40727
6	3369.641	74.14911	3.516587	22.33431
7	3472.502	72.36356	3.935411	23.70102
8	3553.677	71.05881	4.242447	24.69874
9	3618.114	70.08411	4.472056	25.44383
10	3669.490	69.34325	4.646640	26.01011
11	3710.593	68.77251	4.781149	26.44634
12	3743.562	68.32822	4.885862	26.78592
13	3770.061	67.97953	4.968044	27.05243
14	3791.395	67.70411	5.032956	27.26294
15	3808.591	67.48546	5.084488	27.43005

3.8 Discussion

As highlighted previously, maize production in South Africa has a significant influence on temperature. The relationship is bidirectional because it only runs from maize production to temperature and from temperature to maize production. Temperature is one of the inputs for the production of maize hence its influence on maize production is expected (Mendelsohn and Dinar, 2009; Mikemina, 2013). However, the results also suggest that maize production have an influence on temperature. The reason that can be tied to this is that agricultural activities linked to maize production may be emitting GHGs that in turn lead to global warming. This result is similar to those of Igwe *et al.* (2013) who investigated the causality between crop production and climatic variables in Nigeria. Their results suggest bidirectional causality between maize production and temperature. Besides the differences in climatic conditions between Nigeria and South Africa, the most important point to note is that maize production is having an influence on global warming. Other proponents like Pryor *et al.* (2017), who studied the impact of agricultural practises on GHG emissions in South Africa, also support the findings of this study, namely that agricultural activities are leading to global warming. Their results suggest that temperatures are rising owing to activities such as mechanization and fertilizer applications that have occurred in the past and this continue to happen. Many of these activities are carried out in the production of maize, therefore this study suggests that current maize production activities are posing a threat to the climate.

Considering the relationship between rainfall and maize production, the results suggest a no causality between the two which is somehow surprising since rainfall is one of the crucial inputs in the production of maize (Mikemina, 2013). However, rainfall effects may not be felt in the event that irrigation is being practiced. The occurrence of other natural disasters like floods in one might increase the water table hence increasing the availability of irrigation water in the following years given low rainfall amounts were to be recorded (Kumar et al., 2018). In this instance, the effect of low rainfall amounts may not be significant on the production of maize since plenty of irrigation water will be available to outset the water shortages in plants.

The forecast shows that maize production in South Africa continues to have an impact on both climatic variables (temperature and rainfall), thereby leading to global warming. Literature (IPCC, 2013; Ziervogel *et al.*, 2014; Fodor *et al.*, 2017) supports these findings. The changes that are going to be realized in climatic variables in the future owing to current maize production activities are referred to as a change in climate (Savitsky, 2017). The change in climate has some detrimental effects on crop production (maize in particular) in the country. This is supported by the forecast results that also show that there will be some significant impacts (more than 10% magnitude of impact from temperature increases) on maize production. This, therefore, supports the findings by Okoloye *et al.* (2013) that climate change has worrisome effects on crop production and the agricultural sector at large. Because maize production is a significant component of the agricultural sector, negative influences on it will result in problems such as a decrease in agricultural employment, loss of welfare of maize farmers, and loss in agricultural exports, thereby weakening the trade balance. As a result, efforts to improve agricultural production must be sustainable enough to ensure some socio-economic benefits all the time.

3.9 Conclusion and recommendation

The study concluded that South African maize production has a significant influence on the climate in South Africa. This shows that current farming activities are leading to temperature rises thus posing an enormous threat to future maize production. Given this situation, it will be beneficial if farmers increase their rate of adaptation to climate change. However, it is argued in the literature that some of these coping strategies to climate change may reduce agricultural output, which might raise the problem of food shortages. For instance, Powlson *et al.* (2014) stipulated that no-till agriculture can be beneficial to soil quality, but it has no capacity to mitigate the impact of climate change. As a solution, literature advocate biochar applications to soils as it is effective in reducing GHG emissions through carbon sequestration of soils, thereby mitigating climate change (Ibrahim *et al.*, 2017; Sun *et al.*, 2018). Homagain *et al.* (2015) recommended the use of biochar in farming as it mitigates climate change by around 15%. However, Joseph *et al.* (2018) argue that biochar tends to react to soil nutrients and starts competing with plants for nutrient uptake instead of providing nutrients, thus impeding the growth of plants. Besides biochar applications, adapting to organic agriculture can also be beneficial as it limits agricultural emissions, but its effectiveness in attaining higher productivity is questioned. Following from FAO’s recommendations, this study also recommend the adaptation of climate-smart agriculture as it enhances productivity and reduce climate change.

Chapter 4

Physio-economic impacts of climate change on maize production in South Africa

4.1 Introduction

Climate change has been a threat on the past, current and future maize production as a result of direct effects of fluctuations in climatic elements (Porwollik *et al.*, 2017). As highlighted in both the fourth and fifth assessment reports of the International Panel on Climate Change (IPCC), the projected change in climate events will have serious consequences for food security in dry weather countries like South Africa (Mangani *et al.*, 2018). In South Africa, maize is the main grain crop and is the staple food for most of the nation's population; it is also used as feed for livestock. Thus, any change in climate that influences the production of maize would result in some serious socio-economic problems such as food insecurity, conflicts, high crime rates and poor economic growth. It is therefore important to quantify the effects of climate change on maize yield and the maize industry in general to help in formulating effective and efficient mitigation and adaptation practices.

Literature has quantified the impact of climate change on different scales using various methodologies in South Africa (Abraha and Savage, 2006; Benhin, 2008; Walker and Schulze, 2008; Estes *et al.*, 2013; Nxumalo, 2014; Mangani *et al.*, 2018). These studies suggest different results regarding the impact of climate change on maize yield in the country. Some studies suggest a negative influence of warming, whereas others suggest a positive influence of warming on yield. These differences could be attributed to different factors such as the climate scenario used, the approach used, and whether adaption was taken into consideration or not.

This study therefore quantified the average change in maize yield caused by climate change in South Africa using meta-analysis that combined results from 34 studies, summarizing a range of outcomes and at the same time assessing the consensus. The study further assessed the effects of climate change on the gross value of maize (maize revenue) to quantify the marginal impacts of climatic variables on the maize industry in general. This was done using the Ricardian analysis which is used to estimate the impact of climate change on agricultural incomes (Mendelsohn *et al.*, 1994). Two questions are therefore answered in this study: what is the average estimated impact of climate change on maize yield in South Africa? and what is the impact of climate change on the gross value of maize in South Africa?

4.2 Research methods

Two methods (meta-analysis and Ricardian approach) were used in this study. The meta-analysis, as mentioned previously, was used to estimate the impact of climate change on changes in maize yield. On the other hand, the Ricardian approach was used to estimate the marginal impacts of changes in climatic variables on the gross value of maize in South Africa. The following sections describe the methodologies used in this study.

4.2.1 Meta-analysis methods

In order to arrive at the average change in maize yield driven by a change in climate, a meta-analysis of studies that focused on estimating the change in maize yield owing to changes in climatic conditions in South Africa was used. The meta-analysis in this study combined and compared results from several studies, and reached the estimated average change in yield as a result of global warming. Many of the steps taken in this study followed Challinor *et al.* (2014), who studied crop yields under climate and adaptation on a global scale. An extensive search for studies was done using search terms (climate change assessment, climate impacts, impact assessment, climate change impacts, effect of climate change, maize, crop productivity, farm yields, and crop yields in South Africa). All the studies used in this study were extracted from three data bases (Scopus, Web of Science and Google Scholar). The search yielded 161 studies, and owing to the inclusion and exclusion criteria that were employed; only 34 studies (presented as appendices) were selected to run the analysis. The selection process of the studies used in this study is shown in Figure 4.1. After identifying the relevant studies, extraction of the reported percentage changes in yield by each study was done, and then the average change in yield using 500 bootstrapped samples was calculated. Bootstrapping was used because studies that reported changes in yield were scarce, therefore this technique helped in reaching a mean that is close to that of the true population (Hutchison *et al.*, 2018; Cheng and Chen, 2019).

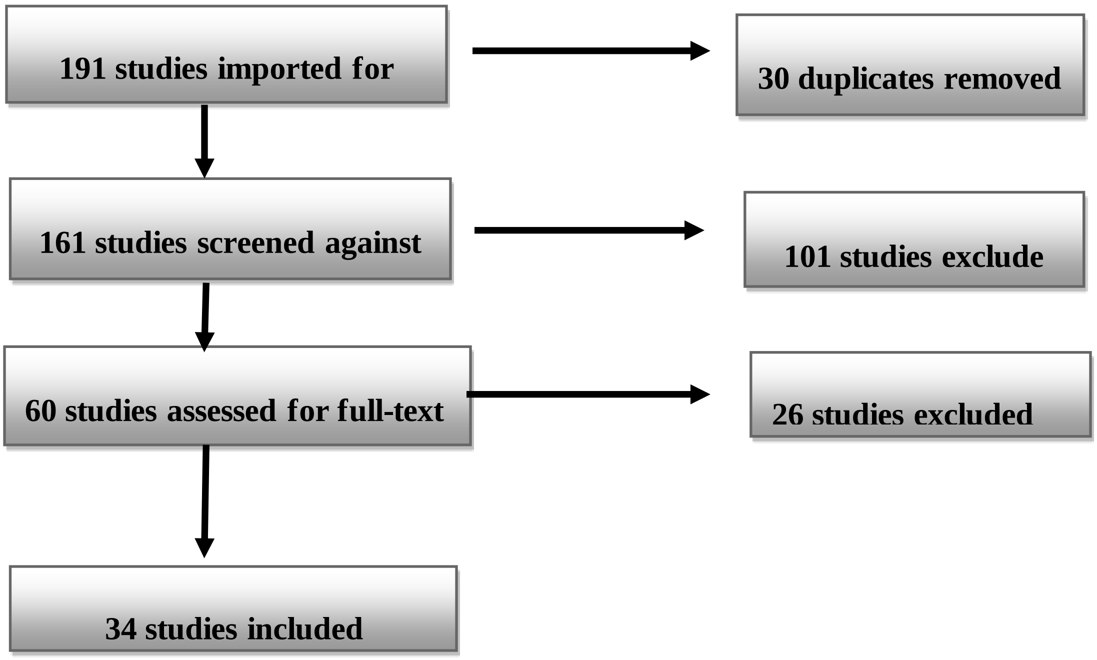


Figure 4.1: Study selection process

Given that the extracted results from the selected studies were divergent, this study also fitted an ordinary least squares model to assess any significant effects on maize yield change from two continuous explanatory variables (temperature change and rainfall change) and three categorical explanatory variables (adaptation, model type and scale). The Gaussian distribution and homogenous tests, as well as the multicollinearity test between temperature and rainfall, were also carried out to ensure reliable interpretation of results. These tests are explained later in this chapter. The following equation is the fitted OLS model to the influences of the factors mentioned earlier on the reported change in maize yield by different studies.

$$\Delta Y = \beta_1 TMP_i + \beta_2 RFLL_i + \beta_3 ADP_i + \beta_4 MOD_i + \beta_5 SCL_i + \varepsilon_i \qquad (4.1)$$

where TMP_i is temperature; $RFLL_i$ is rainfall; ADP_i is adaptation to climate change (0 if not considered and 1 if considered); MOD_i is model used (1 if statistical model, 2 if climate model and 3 if crop model); SCL_i is the scale of the study (1 if done on a small scale, 2 if done on a medium scale and 3 if done on a large scale.

4.2.2 The Ricardian approach to the impact of climate change

The Ricardian model was derived from David Ricardo's studies concerning land rents (Mendelsohn *et al.*, 1994; Mendelsohn and Dinar, 2009). The model is regarded as the best model that measures the impact of climate change on agriculture. The reason for this is because the Ricardian model normally considers farmers' full range adaptation strategies as a black box by performing a cross-sectional regression of land values or net revenues on climate averages and other control variables, as mentioned previously (De Salvo *et al.*, 2013). The model assumes that land rent would reflect the long-term net productivity of farmland. Mendelsohn *et al.* (1994) simplified this principle by developing a model that is structured as follows:

$$v = \sum_{i=0}^{n} PiQi\,(X, C, S, G, H) - \sum PxX \tag{4.2}$$

where v is the net productivity of farmland, P_i is the price of crop i, Q_i is the output of crop i, X denotes purchased inputs excluding land, C is the vector of climatic elements, S denotes soil variables, G is for economic variables, H denotes water flow and P_x represents input prices in the model.

It is important to note that the net productivity of farmland is mainly dependent on revenues (P_iQ_i) produced from farm production. High values of total revenue imply a high value of net productivity, therefore in this study we use gross value of maize (maize revenue) as the dependent variable in the model as data of net productivity of farmland is not available at national level. It is therefore assumed that the higher gross value of maize implies higher net farm incomes, presuming that other things are constant. This idea was adopted from Mikemina (2013), who studied the impact of climate change on Togo's agricultural performance at a national level. The Ricardian model used in this study is therefore specified as follows:

$$GVM = \alpha_0 + \sum_{j=1}^{m} [\,\alpha_j T_j + \beta_j T_j^2 + \delta_j P_j + \gamma_j P_j^2] + \sum \theta_j\, E_j + \mu \tag{4.3}$$

where GVM is the gross value of maize, T_j is temperature, P_j is rainfall, E_j denotes some other variables that affect the total revenue of maize, including irrigation, agricultural employment, agricultural machinery and area planted by maize.

Irrigation was included to consider farmers' adaptation strategies in the face of climate change, thereby removing the problem of over or under estimation. The quadratic terms of climatic variables in the equation capture the nonlinear shape of the net revenue (proxied by gross value of maize) climate response function, indicating how marginal effect will change as we move away from the mean (Mendelsohn *et al.*, 1994). The positive and negative values of the quadratic function represent U-shape and hill-shape respectively. According to Huong *et al.* (2018), temperature is normally expected to have a hill-shaped relationship with the revenues, whilst rainfall is expected to have a U-shaped relationship. Since we test the marginal impacts of climate variables on revenue, we derived the equations for the marginal impacts as follows:

$$MI_T = \left[\frac{dR}{dT}\right] = \alpha_j + 2\beta_j T \tag{4.4}$$

$$MI_P = \left[\frac{dR}{dP}\right] = \alpha_j + 2\gamma_j T \tag{4.5}$$

The change in revenue because of climate change can, therefore, be expressed as ΔMI, which is specified as follows:

$$\Delta MI_T = MI_{T+1} - MI_T \tag{4.6}$$

$$\Delta MI_P = MI_{P-1} - MI_P \tag{4.7}$$

Where subscripts (T+1) and (P-1) represent an increase in temperature and a decrease in rainfall respectively. Letting (T+1) =g and (P-1) =f and then substitute equations 4.4 and 4.5 into equations 4.6 and 4.7 will yield the following results for the change in marginal impacts after simplifying.

$$\Delta MI_T = 2\beta_j(T_g - T) \tag{4.8}$$

$$\Delta MI_T = 2\gamma_j(T_f - T) \tag{4.9}$$

The marginal impacts of changes in climatic variables (+2^{0}C temperature and -15% rainfall) were estimated using the equations 4.8 and 4.9 shown above.

Definition and justification of variables

*Gross value of maize $LGVM_t$ (Dependent variable)***:** This is the value of the total maize produced, which is calculated as price (producer) multiplied by the total quantity of maize produced in the nation, measured in South African Rand. This is also known as total revenue from maize production. The data for this variable was collected as annual data from DAFF abstract publications of several issues. The Ricardian model determines the net land revenues produced by farmers from the productive use of their land in the presence of climate change (Mendelsohn and Dinar, 1999). This variable was transformed into natural logarithms, hence the name *LGVM.*

Climatic elements (Temperature $TEMP_t$ and Rainfall $RFLL_t$): Temperature and rainfall were recorded as annual temperature averages and annual rainfall averages respectively. The averages were calculated from the monthly data of temperature and rainfall collected from SAWS and World Bank Data archives. Temperature was expected to have a negative effect on the value of maize, whilst rainfall was expected to have a positive influence. Literature justifies the inclusion of climatic elements when modelling the impact of climate change on agricultural revenues because they are regarded as inputs in the production of maize, and they determine how much is going to be produced (Mendelsohn and Dinar, 2009; Mikemina, 2013; Nhemachena *et al.*, 2014).

Area planted by maize AL_t: Area planted by maize is the total area of land used for maize production, which is measured in hectares. The classical economics of Adam Smith and David Ricardo suggests that land is one of the factors of production; thus, it determines how much output will be produced. As a result, the variable is expected to have a positive relationship with the revenues produced from maize production in the Ricardian model.

Price PRC_t: It is the producer price (in Rands) per each ton of maize produced in South Africa, using 2010 as the base year price. The higher the price, the higher the value of the good in question, thus a positive relationship between prices and gross value of maize was expected from the Ricardian analysis. The data for maize prices was collected from the 2018 DAFF abstract.

Irrigation $LIRR_t$: Given the global rise in temperature generated by climate change, farmers tend to adapt by irrigating their farms to continue producing high yields. Irrigation is therefore expected to have a positive correlation with the gross value of maize, as the more irrigated the land is, a higher maize output will be produced, which will translate into higher revenues from maize production. The unit of measurement for irrigation is, therefore, the total irrigated land as a percentage of total arable land. This variable was also presented in natural logarithms in the analysis as the name *LIRR*.

Agricultural machinery AM_t: Agricultural machinery is the machine technology used on a farm to help with farming production (Mikemina, 2013). The number of tractors was used as the proxy for agricultural machinery in this study. It was expected to have a positive impact on the gross value of maize, thus an increase in the number of tractors is expected to increase the value of maize in South Africa. The data for this variable was collected from the World Bank data atlas.

Data sources and type

This study used time series data for the period 1987-2018 for all the variables used in the Ricardian model. This time series data was used to investigate the economic impacts of climatic variables on the maize industry. All the data were obtained from secondary sources of several issues published by Index Mundi, World Bank, DAFF and the South African Weather Services. Table 4.1 provides a summary of the definition of variables used in the Ricardian model, their unit of measurements, as well as the priori expectations for all the exogenous variables used.

Table 4.1: Definition of variables

Variable	Definition	Unit of measurement	Expected sign
LGVM	Gross value of maize	Rand per ton	N/A
TEMP	Temperature	Degree Celsius (^{0}C)	(-)
RFLL	Rainfall	Percentage (%)	(+)
APM	Area planted of maize	1000ha	(+)
PRC	Producer prices of maize	Rand per ton (2010=100)	(+)
AM	Agricultural machinery	Number of tractors	(+)
LIRR	Total irrigated land as a percentage of arable land	1000ha	(+)

Model diagnostic tests

The augmented Dickey-Fuller (ADF) as well as the Phillips-Perron test were used to detect the stationarity of the data, and the decision was considered at 1%, 5% and 10% levels of significance. Non-stationary data results in spurious regressions, therefore series that were not stationary were differenced to make them stationary. This test is very important when using time series data, so all the variables used in the Ricardian model were tested for stationarity. Table 4.2 presents the stationarity test results, suggesting that 4 variables were stationary at level and the other 2 became stationary after first difference.

Table 4.2: Stationarity test results

Variables	Test in	ADF		PP	
		t-stat	p-value	t-stat	p-value
LIRR	Level	-3.284	0.0876*	-2.535	0.1174
	1st difference	-7.590	0.0000***	-9.042	0.0000***
LGVM	Level	-4.341	0.0096***	-8.756	0.0000***
	1st difference	N/A	N/A	N/A	N/A
AM	Level	-2.380	0.1557	-1.008	0.9283
	1st difference	-4.406	0.0016***	-5.178	0.0012***
PRC	Level	4.810	1.0000	5.197	1.0000
	1st difference	-4.170	0.0029***	-3.894	0.0058***
TMP	Level	-3.709	0.0053***	-3.316	0.0166**
	1st difference	N/A	N/A	N/A	N/A
RFLL	Level	-9.687	0.0000***	-9.688	0.0000***
	1st difference	N/A	N/A	N/A	N/A

*where ***, ** and * represent 1%, 5% and 10% levels of significance respectively*

A multicollinearity test was done using the correlation matrix to ensure that there are no highly correlated variables in the model. To investigate the absence of multicollinearity, a rule of thumb, which states that the correlation coefficient of both series should be less than 0.8, was used. With multicolline arity, it is difficult to isolate the individual effects of the explanatory variables to the dependent (Gujarati, 2004). The results for multicollinearity are presented as appendices of this study.

The normality assumption is that errors must be normally distributed with mean E (μt) = 0. If the error terms are not normally distributed, incorrect confidence intervals can be made. The Jarque- Bera (JB) test was used as a formal test for normality, and decisions were made guided by the Jarque-Bera statistic, which is supposed to be close to zero, and its probability, which is supposed to be above 5% level of significance to reject the null hypothesis of no normality (Gujarati, 2004). As shown in Table 4.3, the probability value (0.8084) suggest that there are normally distributed residuals from the estimation, in this manner satisfying the Gauss Markov theorem.

The varying variance of the error term inflates the confidence intervals, leading to the acceptance of a false hypothesis; thus estimators will be inefficient and will be considered unreliable (Gujarati, 2004). To test for heteroscedasticity, the Breusch-Pagan-Godfrey test was used in this study, and the null hypothesis of non-varying variance was either rejected or accepted guided by the 5% level of significance. The results presented in Table 4.3 suggest that the null hypothesis may not be rejected (p-value = 0.6616), meaning the variance of the errors from the estimation is not varying.

A test for autocorrelation is also important when dealing with time series data. A model with autocorrelation may result in a very high coefficient of determination, which is a sign of some spurious regressions. This will result in some unreliable estimation of results, therefore it is important to make sure that autocorrelation is absent from the model. The Breusch-Godfrey test was used to test for autocorrelation in this study. The results (p-value = 0.7173) from this test suggest the absence of autocorrelation from the estimation, consequently, the results produced were reliable interpretations.

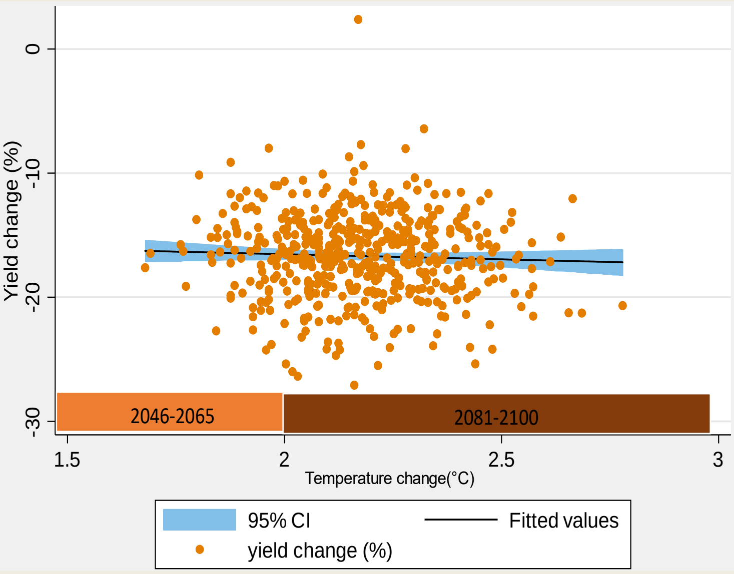
The Ramsey RESET test is used to test the validity of the whole model, and the probability value of the t-statistic was considered guided by the significance level of 5%. Any value of the probability value less than 5% suggests a model misspecification. However, the results given in Table 4.3 show that the model is correctly specified, as the probability (p-value = 0.3769) is above 5%. This therefore ensures that the results estimated from the model were valid for interpretation.

Table 4.3: Model diagnostic test results

Diagnosed problem	Test used	Statistic	P-value
Autocorrelation	Breusch-Godfrey	F-stat = 0.3378	0.7173
Heteroskedasticity	Breusch-Pagan-Godfrey	F-stat = 0.7333	0.6616
Normality	Jarque-Bera	JB stat = 0.4252	0.8084
Model specification	RESET	t-stat = 0.9027	0.3769

4.3 Results and discussion

Physical impacts of climate change on maize production



Test statistic	Yield change	
Mean Δ	-16.67	
Maximum Δ	-30.05	
Minimum Δ	-5.13	
Std dev	3.53	
Confidence interval	-23.56	-9.81

Figure 4.2: Percentage change in yield as a function of temperature; shaded blue band indicates the 95% confidence interval.

As shown in Figure 4.2, the majority of studies reported yield changes that are above -10%, indicating that the chances of avoiding losses in maize yield in South Africa are very limited. The maximum change in maize yield owing to warming in South Africa is reported to be around -30.1%. The average change in yield as a result of climate warming is about -16.7% (calculated from 500 bootstrapped samples) at 95% confidence interval (shown by the blue bend), and this effect continues to rise as the temperature increases. Effects are more on temperatures above 2^{0}C, which are expected in the 2081-2100 year range (highlighted brown region) as compared to the 2045-2065 year range (highlighted orange region), where temperatures are expected to rise by no more than 2^{0}C according to a RCP 8.5 climate change scenario. These results comply with Challinor *et al.* (2014), who estimated the impacts of climate change and adaptation on various crops, including maize, at a global scale using the bootstrapping sampling technique.

As a complement to the bootstrapped average changes in maize yield from various studies in South Africa, a general linear model was fitted to assess the significance of factors (model used, adaptation, temperature, rainfall and scale) on the reported changes in yields. However, the model should be interpreted with caution since there was no attempt to weight the studies by quality or their representativeness of major production areas. As shown in Table 4.4, there is a high significance (t = -3.72; p-value = 0.001) of temperature changes considered by a study of the estimation of changes in maize yield in South Africa. A 1^0C change in temperature considered would result to an average of 8.27% yield loss. Furthermore, the model inferred a significant (t = 1.76; p-value = 0.089) positive influence of rainfall with a 0.79% change in rainfall. It is therefore important to take note that the climate change scenario considered when estimating the impact of climate change is important. Furthermore, adaptation was also highly significant (t = 2.74; p-value = 0.011), showing the importance of considering adaptation when estimating the impact of climate change. Model type and scale were found not to be statistically significant in explaining the various results found by different researchers when estimating the impacts of climate change.

Table 4.4: Factors influencing the reported results of climate change impact

Variable	Coefficient	t-stat	p-value
Temperature Δ	-8.27	-3.72	0.001^{***}
Rainfall Δ	0.79	1.76	0.089^{*}
Adaptation	13.84	2.74	0.011^{**}
Model type	0.64	0.34	0.735
Scale	-1.34	-0.22	0.831

where ***, ** and * represent significance at 1%, 5% and 10%.

Economic impacts of climate change on maize production

Given the physical impact of climate change on maize production presented above, the analysis was taken further to estimate the effects of warming on the gross value of maize (proxy for farm incomes). As shown in Table 4.5, based on historical data, rainfall (RFLL) has a significant (t = 1.97; p-value = 0.0616) influence on the gross value of maize, presuming that other factors are constant with a percent increment associated with a 0.23% increase in the gross value of maize. Rainfall also has a significant (t = -1.87; p-value = 0.0743) non-linear relationship with the gross value of maize. This means that, at some level, increase rainfall has a negative effect on farm income owing to flooding, for example (Mikemina, 2013). In addition, temperature has a negatively significant (t = -3.19; p-value = 0.0042) relationship with the gross value of maize, with an approximate loss of 52.17% in the gross value of maize per 1^0C. In addition, temperature has a significant (t = 3.23; p-value = 0.0039) non-linear relationship with the gross value of maize, which means both high and low temperatures are not good for the maize industry. Furthermore, other variables (irrigation, agricultural machinery and price) were statistically different from zero, showing some positive influences on the gross value of maize in South Africa.

Table 4.5: Effects of climatic variables on the gross value of maize based on historical data

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RFLL	0.227758^{*}	0.115635	1.969628	0.0616
RFLL2	-0.002838^{*}	0.001514	-1.873725	0.0743
TMP	-52.17522^{***}	16.33244	-3.194576	0.0042
TMP2	1.449594^{***}	0.449340	3.226049	0.0039
LIRR	2.454156^{***}	0.391291	6.271949	0.0000
DAM	0.041215^{***}	0.012829	3.212699	0.0040
DAL	-3.199907	4.466607	-0.714641	0.4823
DPRC	0.001029^{***}	0.000252	4.082278	0.0005
C	451.0853^{***}	148.1946	3.043871	0.0060

where ***, **, * represent significance at 1%,5% and 10% levels

From the estimation presented in Table 4.5, the impacts of climate change were therefore estimated using representative concentration (RCP) 8.5 climate change scenario, which states that temperature will rise by 2^{0}C-3.7^{0}C and rainfall will decrease by 15% between 2046 and 2100. Looking at the margins estimated at means, the marginal effect of a 15% decrease in rainfall is statistically significant (t = 7.34; p-value = 0.000), showing a 13.11% decrease in the gross value of maize at 95% confidence interval. Similarly, the marginal effect of a 2^{0}C increase in temperature is statistically different from zero (t = -2.75; p-value = 0.012), suggesting a decrease of 89.2% in the gross value of maize in South Africa. On average, climate change is therefore estimated to reduce the gross value of maize by about 38% between 2046 and 2100, *ceteris paribus*. The results of the marginal impacts of climate change are shown in Table 4.6.

Table 4.6: Marginal impacts of an increase in temperature by 2^{0}C and a fall in rainfall by 15% on the gross value of maize in South Africa

Variable	Margin	Std. Err.	T	P>|t|	[95% Conf. Interval]	
Rainfall	13.11083^{***}	1.786654	7.34	0.000	9.395277	16.82638
Temperature	-89.20066^{**}	32.46041	-2.75	0.012	-156.7058	-21.69555
All	-38.04492	N/A	N/A	N/A	N/A	N/A

where *** and ** represent significance at 1% and 5% respectively

4.4 Discussion

This is the first study to investigate both the physical and economic effects of climate change on maize production in South Africa using meta-analysis (for physical impacts) and Ricardian analysis using time series data (for economic impacts). Many studies (Gbetibouo and Hassan, 2005; Benhin, 2008; Nxumalo, 2014) that modeled the impact of climate change using the

Ricardian analysis were done as small-scale studies, and these might not represent the true effects of climate change on maize production at national level. As a result, this study modeled the impacts of climate change on maize production using the Ricardian model, making use of secondary data collected at national level to arrive at the estimated impacts at national level.

In terms of at physical impacts, the results from meta-analysis show that yield is going to fall by an average of 16%, amounting to a serious threat to the South African maize industry. Given that maize is the main grain crop supporting many livelihoods in South Africa, the projected decrease in yield will constitute some challenges regarding ensuring food security and reducing poverty (Jones and Thornton, 2003; Abraha and Savage, 2006; Lobell and Burke, 2010). Yet again, this decrease in yield owing to climate change is contrary to the National Development Plan (NDP) goal of creating a food surplus, with many contributions coming from the small-scale farmers. As highlighted by the World Bank (2017), the South African population is growing at an annual rate of 1.2%, therefore given the yield decreases projected in this study, some problems associated with hunger such as poor nutrition and conflicts will also potentially rise, making the country ungovernable.

Looking at the economic impacts of climate change on maize production, the results from the Ricardian analysis used in this study reveal that maize revenues are more sensitive to marginal changes in temperature than changes in rainfall. This supports the results by Gbetibouo and Hassan (2005), who measured the economic impact of climate change on major South African field crops. This result has a major implication on the quick adoption of heat tolerant maize varieties as compared to the drought tolerant counterparts. The marginal effects of climatic variables on maize revenue estimated in this study show that on average the maize revenue will fall by around 38%, crippling the maize industry of South Africa. A poor performing maize industry and related economic problems such as high unemployment and poor economic growth are already being experienced by the country.

4.5 Conclusion and recommendations

As appraised by several studies (Du Toit *et al.*, 2002; Mikemina, 2013; Challinor *et al.*, 2014; Dale *et al.*, 2017; Mangani *et al.*, 2019), climate change has been acknowledged as a serious global concern for food production. This problem translates into serious effects on human life, for example food insecurity and conflicts owing to food shortages. Climate change therefore remains a matter of concern for policy makers owing to its impact on livelihoods. As a result, this study compiled the estimated changes in yield reported by different studies in South Africa to reach a single estimated average change in maize yield as a result of climate change. The study went further to estimate the economic impacts of climate on maize revenue at national level to give a clear guide to policy makers regarding what to look at when addressing the effects of climate warming in South Africa. The results from the estimations suggest significant losses in both maize yield and revenue in South Africa from 2046 onwards, with many effects being driven by temperature warming rather than rainfall decreases. This study therefore recommends the adoption of heat resistant maize varieties in South Africa. Given the challenges faced in this study, it is also recommended that future studies investigating the impacts of climate change on maize production report the associated changes in yield, the assumed climate change scenario, and consider adaptation in order to avoid over- or under-estimation of changes in yield. It is also recommended that data enumerators should start reporting data for farm net revenues at national level in order to guide future studies to be carried out at country level.

Chapter 5
Summary, Conclusion and Policy Recommendations

5.1 Introduction

This chapter presents a summary of the study and the conclusions drawn from it. The chapter further outlined the policy recommendations, as well as suggestions for further studies.

5.2 Summary

Climate change is a serious global threat to humanity. This is through its warming effects to sectors such as agriculture which provides food for most of the world population. In this case, yields of major crops such as maize, rice and wheat will become volatile due to increased climate variability thus driving up the price volatilities of food. The food price volatilities are not favorable especially in Africa where many people are poor. Climate change does not only undermine crop yields, it also makes other crops produced less nutritious; cause geographical shifts in fisheries; increased number of pests that thrive in warmer environments; and increased farm loses (due to natural disasters) in cases where farmers are not insured. As a result, there will be some developmental challenges which lead to poor economic performance which is a characteristic of many African countries. In South Africa, agriculture contributes less than 2% to the country's GDP which means that its function of backward and forward linkages to the other sectors of the economy are not well performed.

However, it has been empirically proven that the change in climate is mainly anthropogenic (human induced) through various economic activities some of which include agricultural practises. Conventional crop farming cause large emissions of carbon from the soils, carbon from use of fossil fuels (direct and indirect) into the atmosphere and nitrous oxide emissions due to heavy use of fertilizers and other agricultural chemicals. The production of maize in South Africa is highly conventional hence for policy guidance, the study analyzed the causal relationships between climatic variables and maize production and also evaluated the physical and economic impacts of climate change on maize production in South Africa. The empirical Chapters Three and Four made use of Granger analysis and combined meta and Ricardian analysis respectively to meet the objectives of the study.

The first objective was to examine the causal relationships that exist between climate change and maize production in South Africa using time series data for the period 1924-2016. As mentioned previously, the VAR Granger causality analysis was used to evaluate this objective since it tests for both the existence of unidirectional causality of one variable to the other and the existence of a bidirectional causality that may exist between two variables. By this, the first objective attempted to determine whether maize production has a significant influence on temperature and rainfall, or there is only one direction causality whereby only changes in climate influence maize production, without maize production affecting the climate through the GHGs emissions. Under the same objective, further analysis was carried out using the variance decomposition to come up with a 15-year forecast of the relationships that exist between climatic variables (temperature and rainfall) and maize production in South Africa.

The second objective of the study was to examine the physio-economic impacts of climate change on maize production in South Africa. The main purpose of this objective was to quantify the impacts of climate change on the maize industry in South Africa both in physical and in monetary terms. Two methods were applied to attain this objective. A meta-analysis was used to identify the impacts of a change in climate on maize yields (physical impacts), and the Ricardian analysis was used to evaluate the influences of climate warming on maize revenues (economic impact).

The meta-analysis used in this study made use of 34 selected studies from Scopus, Web of Science and Google Scholar, and applied bootstrapping technique to calculate the average change in yield due to climate change. Inside the meta-analysis methodology, an OLS regression equation was fitted to determine the factors influencing the reported results of changes in maize yield. The fitted OLS regression equation tested the significance of temperature, rainfall and other three categorical variables (scale of study, model used and adaptation) in explaining the reported change in maize yield.

The Ricardian analysis made use of secondary time series data for the period 1987 through 2018 and evaluated the influence of climatic variables (temperature and rainfall) on the gross value of maize in South Africa given a climate scenario of RCP 8.5. This analysis also included irrigation, producer prices of maize, agricultural machinery and area planted of maize as other explanatory variables in the gross value of maize equation. The effects of temperature and rainfall were determined using the marginal effect analysis which compared the yield effects of temperature (+2^0C) and rainfall (-15%) to be realised in future as projected by the RCP 8.5 to the yield effects of current climatic conditions.

5.3 Conclusion

The results from the Granger causality tests suggest that maize production has an influence on the climate, as indicated in Chapter Three. Maize production was significantly Granger causal to both temperature and rainfall with a surprisingly no reverse effect of climatic variables to maize production in South Africa. Further analysis of the forecast error variance decomposition suggests that climatic variables, on the other hand, have a significant influence on maize production in the long run and no short significant short run influences were detected. The study therefore concluded that current maize production activities in South Africa contribute to climate change, and the realized climate warming will influence production in the long run. This means current maize production activities will undermine future food production which is a threat to humanity given rate at which the population is growing every year.

It is also suggested from the meta-analysis that there will be an average decline in maize yield of more than 15% due to climate warming, as presented in Chapter Four. Furthermore, the study also discovered that there will be significant losses in maize revenues of about 38% by 2065 due to a climate scenario of +2^0C increase in temperature and -15% decline in rainfall, as suggested by the marginal effects calculated from the Ricardian analysis. Given these results, the study also concluded that climate change has serious negative impact to the maize industry in South Africa. This would undermine maize farmers livelihoods and the South African economy at large hence immediate action is required.

5.4 Policy Recommendations

Based on the results generated in this study, it is recommended that maize farmers increase the usage of heat tolerant maize species (for example open pollinated varieties) as projections show that heat will decrease yields and revenues. There should be increased research and development to come up with heat resistant maize varieties which farmers can choose from. This will help enhance the maize yields under hot climatic conditions which will help sustain food production.

There should also be increased irrigation in maize farming so that the effects of temperature increases will be lessened on the production of maize. This will help reduce the effects of water loses in crops due to temperature warming and reduced rainfall. However, setting up irrigation schemes requires large capital outlay and as a result, investments in agriculture should be improved to make some of these mitigation strategies possible.

Further, there should be increased crop insurance to cover for unexpected losses that may be caused by extreme weather conditions such as droughts, floods, hailstorms and tornadoes that are witnessed because of climate change. This will help farmers to continue sustain their livelihoods in the world of changing climate.

In addition, it also recommended that climate smart practices be adopted when carrying out maize production to reduce the amount of GHGs emitted into the atmosphere that cause climate change. These activities can be termed climate smart agriculture, and they include biochar soil amendments, minimum tillage and balanced fertilization.

5.5 Suggestions for further research

It is suggested that further research examine the sustainability of climate smart agricultural activities. This will help in creating more innovative ways that produce more maize to feed the continuously rising population at the same time reducing the rate at which the climate is changing. It is also important for further studies to model causalities between agricultural production and carbon emissions to assess the footprint of agriculture on the climate.

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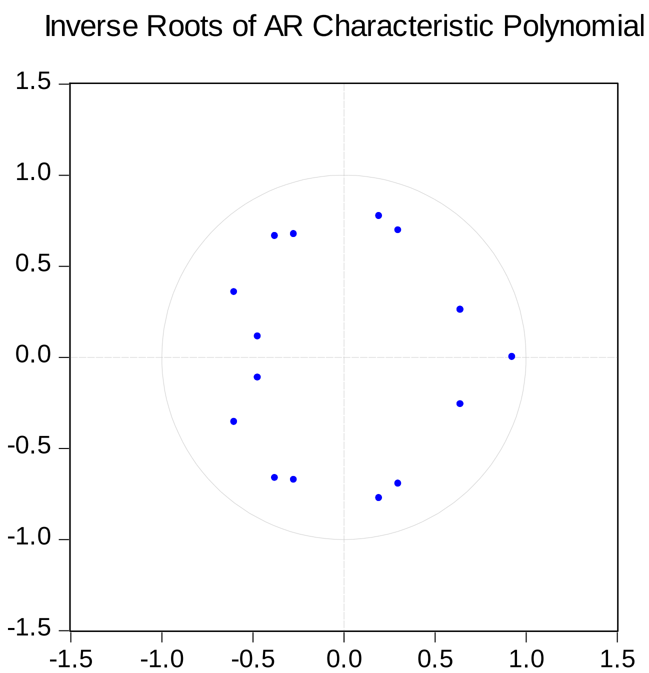
Chapter 6 Appendices

Appendix A: VAR Granger model diagnostic tests

A1. Model stability test



A2. Autocorrelation test

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h

Date: 10/23/19 Time: 12:01
Sample: 1924 2016
Included observations: 87

Lags	LM-Stat	Prob
1	8.996845	0.4376
2	7.985311	0.5356
3	9.495477	0.3928
4	6.108782	0.7290
5	1.509271	0.9971
6	6.554845	0.6834

Probs from chi-square with 9 df.

A3. Normality test

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Date: 10/23/19 Time: 12:06
Sample: 1924 2016
Included observations: 87

Component	Skewness	Chi-sq	Df	Prob.
1	-0.138472	0.278029	1	0.5980
2	0.429101	2.669847	1	0.1023
3	-0.128880	0.240846	1	0.6236
Joint		3.188722	3	0.3634

Component	Kurtosis	Chi-sq	df	Prob.
1	4.037147	3.899316	1	0.0483
2	2.572901	0.661248	1	0.4161
3	2.844634	0.087503	1	0.7674
Joint		4.648067	3	0.1995

Component	Jarque-Bera	Df	Prob.
1	4.177345	2	0.1239

2	3.331095	2	0.1891
3	0.328349	2	0.8486
Joint	7.836789	6	0.2503

A4. Heteroskedasticity test

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)
Date: 10/23/19 Time: 12:15
Sample: 1924 2016
Included observations: 87

Joint test:

Chi-sq	df	Prob.
217.5889	216	0.4569

Individual components:

Dependent	R-squared	F(36,50)	Prob.	Chi-sq(36)	Prob.
res1*res1	0.601880	2.099731	0.0077	52.36357	0.0382
res2*res2	0.354306	0.762111	0.8021	30.82459	0.7130
res3*res3	0.355599	0.766428	0.7971	30.93709	0.7080
res2*res1	0.541090	1.637605	0.0530	47.07481	0.1024
res3*res1	0.379907	0.850920	0.6914	33.05195	0.6096
res3*res2	0.285161	0.554051	0.9671	24.80903	0.9202

Appendix B: Variance decomposition of temperature and rainfall

Variance Decomposition of TMP:

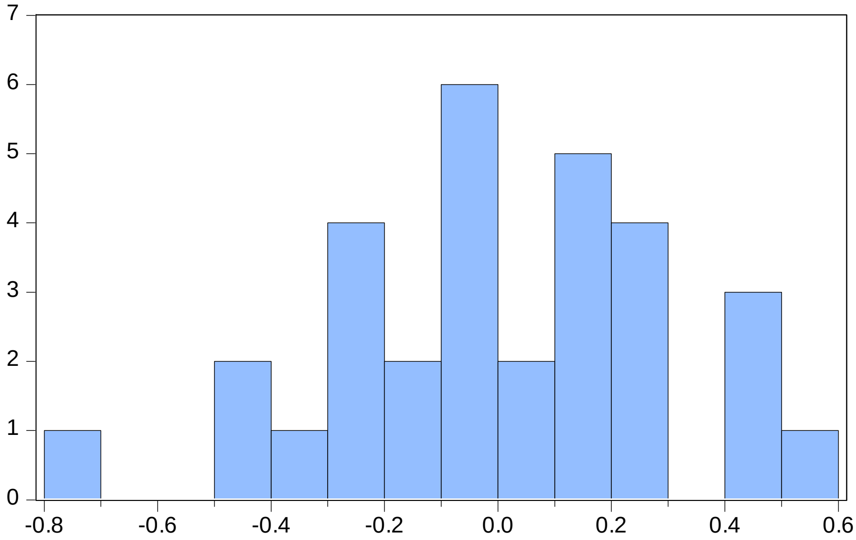
Period	S.E.	DMZQ	RFLL	TMP
1	0.314629	16.04815	11.76894	72.18291
2	0.366806	21.77607	20.21782	58.00611
3	0.370044	21.78907	19.87104	58.33989
4	0.370929	21.69548	20.00860	58.29592
5	0.372383	21.67597	19.86049	58.46354
6	0.385249	22.56427	19.04939	58.38634
7	0.393684	23.65661	18.78693	57.55646
8	0.394613	23.56231	18.83305	57.60464
9	0.395114	23.56269	18.78935	57.64796
10	0.399084	24.06025	18.47022	57.46953
11	0.407395	25.59430	17.76769	56.63801
12	0.412536	26.43171	17.34085	56.22744
13	0.415137	26.65955	17.13962	56.20084
14	0.418190	27.02462	16.93893	56.03645
15	0.422780	27.69195	16.65333	55.65473

Variance Decomposition of RFLL:

Period	S.E.	DMZQ	RFLL	TMP
1	5.654346	16.96411	83.03589	0.000000
2	5.773419	16.45100	83.51474	0.034259
3	6.029832	20.83631	76.57105	2.592638
4	6.156865	22.08941	74.96840	2.942195
5	6.260787	22.42961	73.09865	4.471736
6	6.382198	24.31011	70.60632	5.083569
7	6.473098	25.90708	68.73866	5.354265
8	6.509132	26.35019	68.09576	5.554044
9	6.524468	26.69109	67.77716	5.531748
10	6.585252	27.14791	66.59653	6.255562
11	6.630388	27.47795	65.74848	6.773563
12	6.650012	27.76588	65.36118	6.872938
13	6.664179	27.77527	65.09155	7.133179
14	6.681931	27.89910	64.78802	7.312878
15	6.712139	28.24971	64.22817	7.522110

Appendix C: Ricardian model diagnostic tests

C1. Normality test



Series: Residuals	
Sample 1988 2018	
Observations 31	
Mean	-1.69e-13
Median	-0.008197
Maximum	0.568981
Minimum	-0.772915
Std. Dev.	0.298735
Skewness	-0.284221
Kurtosis	3.077937
Jarque-Bera	0.425217
Probability	0.808473

C2. Autocorrelation test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.337837	Prob. F(2,20)	0.7173
Obs*R-squared	1.013069	Prob. Chi-Square(2)	0.6026

C3. Heteroskedasticity

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.733314	Prob. F(8,22)	0.6616
Obs*R-squared	6.526178	Prob. Chi-Square(8)	0.5885
Scaled explained SS	3.414942	Prob. Chi-Square(8)	0.9057

C4. Ramsey RESET test

Ramsey RESET Test
Equation: UNTITLED
Specification: LGVM TMP TMP2 RFLL RFLL2 LIRR DAL DAM DPRC C
Omitted Variables: Squares of fitted values

	Value	df	Probability

t-statistic	0.902713	21	0.3769
F-statistic	0.814892	(1, 21)	0.3769
Likelihood ratio	1.180182	1	0.2773

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.100009	1	0.100009
Restricted SSR	2.677273	22	0.121694
Unrestricted SSR	2.577264	21	0.122727
Unrestricted SSR	2.577264	21	0.122727

LR test summary:

	Value	df
Restricted LogL	-6.024672	22
Unrestricted LogL	-5.434581	21