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The impact of climate change on agricultural crop distribution in South Africa

Matji, Oska

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The impact of climate change on agricultural crop distribution in South Africa.

Oska Matji

A research report submitted to the Faculty of Science, University of the Witwatersrand, in partial fulfilment of the requirements for the Degree of Masters of Science by Coursework and Research Report.

Johannesburg

March 2015

Declaration

I, Oska Matji, declare that this research report, apart from the contributions mentioned in the acknowledgements, is my own, unaided work. It is submitted for the Degree of Master of Science by coursework and research report to the University of the Witwatersrand. It has not been presented before for any degree or examination to any other University.



(Signature of candidate)

5th day of November 2015

Abstract

Climate change is considered a dominant factor that controls species distribution at a large spatial scale. Changes in climate conditions are expected to have a significant impact on the distribution of maize in South Africa in the coming years. Determining the potential changes in maize distributions is important, as it is a staple crop for the majority of South Africans and contributes significantly to the country's economy. The specific objectives of the study were to 1) determine potential distribution of maize under current and predicted climate scenarios using Maxent, 2) determine how the environmental factors change between current and predicted climatic habitat distributions and their influence on maize distributions in South Africa, and 3) statistically compare present and future distributions of maize to see how current and predicted climate habitats differed. Distribution models for high and low maize producing areas were built in Maxent using Bioclim variables from Worldclim. Predicted changes in distributions were then projected using predicted 2050 climate. Two emissions scenarios, RCP2.6 (low emission) and RCP8.5 (high emission), from HadGEM2ES model were used to predict the climate suitability of maize. Model evaluations showed that models had adequate predictability for maize under different climate scenarios (AUC values ≥ 0.7). Precipitation of warmest quarter (Bio18), precipitation of wettest quarter (Bio16), annual precipitation (Bio12), and maximum temperature of warmest month (Bio5) variables contributed the most to model predictions. The models showed a decrease in suitable areas for maize growth in the Highveld region. Present range area for maize as climate changes from low (RCP2.6) and high (RCP8.5) emission scenarios showed a contraction. Predictive models suggest that the most affected areas under future scenarios is the western part of the Highveld region, which is currently characterized by relatively low mean annual precipitation. However, there was an increase in suitability in the Eastern Cape province. Statistical comparisons of current and predicted climatic niches for maize showed that there was little difference, this indicates that climate suitability of maize will not change significantly due to climate change, but that the geographic ranges where these climatic habitats are found will change dramatically. The capacity to develop strategies that will enable maize to adapt to climate change will be vital for South Africa's agro-ecosystem and food security. The results from this study highlight the possible imposition of climate change on maize distribution and could be useful for future work to minimize the potential negative impacts of climate change on food production.

Keywords: Climate change, food security, maize, Maxent, niche quantification, South Africa**.**

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Chapter 1

Literature Review

Climate change

Climate change is regarded as any significant change in measures of climate that persists over a number of decades (IPCC, 2007). Changes in climate could result from natural phenomena or from human activities (Botkin & Keller, 2012). The Intergovernmental Panel on Climate Change (IPCC) reports have indicated that a change in climatic conditions are primarily due to human activities, like the burning of fossil fuels (Davoudi *et al.,* 2009). Africa is considered to be one of the most vulnerable continents to climate change because of the semi-arid climate. The changing climate will likely make cultivation of crops challenging in Africa, which will adversely affect food security (Boko *et al.,* 2007).

Climate change scenarios are useful to help predict the impacts of climate change on the ecosystem. Scenarios of climate change assist researchers in providing potential outcomes based on a range of variables that contributes to climate change such as social-economic change, rate of technological advance and emissions of greenhouse gases. In the past, the Special Report on Emissions Scenarios (Nakicenovic *et al.,* 2000) developed predicted scenarios to provide speculation of possible climate development as influenced by various factors such as economic growth and technological development. Climate change scenarios are used as tools to determine possible consequences of future climate changes. They are also used as input for climate models to evaluate possible climate impacts and mitigation options (Saelthun *et al.,* 1998). More recently, Representative Concentration Pathways (RCPs) have been developed for use in climate change studies (van Vuuren *et al.,* 2011). The Special Report on Emissions Scenarios (SRES) and the RCPs are set up in different ways. For example, the SRES gives greenhouse gas emission and land-use change pathways, based on assumptions involving socio-economic drivers and technological development. On the other hand, the RCPs use radiative forcing (total measure of anthropogenic emission of greenhouse from all sources expressed in Watts per square meter) gases target levels to make predictions for 2100 (van Vuuren *et al.,* 2011). Radiative forcing estimates are based on the emission of greenhouse gases and other forcing agents such as population growth, economic and technological development (van Vuuren *et al.,* 2011). There are four general RCPs scenarios: RCP2.6, RCP4.5, RCP6 and RCP8.5 (van Vuuren *et al.,* 2011). The first scenario (RCP2.6) is considered to be a low emissions scenario because radiative forcing reaches 2.6 W/m^2 by 2100. In order to attain this low emission level, there would be a need for large reduction in greenhouse gas emissions. Following RCP2.6, RCP4.5 demonstrates a scenario where emissions are stabilized; the radiative forcing does not exceed 4.5 W/m^2 within the year 2100. Another stabilization scenario is RCP6

where total radiative forcing is stabilized after 2100. This is achieved by the introduction of range of technologies and strategies for reducing greenhouse gas emissions. Lastly, the RCP8.5 represents a scenario is defined by increasing greenhouse gas emissions over time (van Vuuren *et al.,* 2011).

In South Africa, there has been an increase in mean annual temperatures by approximately 0.65°C over the past five decades (about 1.5 times the global average; Ziervogel *et al.,* 2014). The changing climate has been reported to affect species distributions and phenology (Hughes, 2000, Parmesan 2006). Maize is susceptible to climate change because precipitation and temperature play an important role in the growth of the crop. As a result this study investigates the impact of climate change on maize distribution in South Africa in 2050 under projected climate change scenarios.

Niche theory

Niche theory states that a range of environmental characteristics enables species to survive in a given environmental or geographic space (Scheiner & Willig, 2011). The ecological niche of a species is considered a key factor that determines and limits the distribution of species (Grinnell, 1917). Further, Hutchinson (1957) defined niches using either a fundamental or realized niche concept. The fundamental niche includes only abiotic factors, whereas the realized niche includes both abiotic and biotic interactions (Kearney, 2006). Fundamental and realized niche concepts are considered to be the foundation of Species Distribution Models (SDMs; Araujo & Guisan, 2006). Wiens *et al.* (2009) suggested that frames of references for SDMs are either either fundamental or realized niche concepts. The purpose of SDMs are to characterize a species' ecological niche and project it into geographical space (Guisan & Thuiller, 2005). There are two general types of species distribution models that correspond to the two different types of defined niches. First, a species distribution model corresponds loosely to the fundamental niche approach is mechanistic, as it uses both the species' intrinsic properties that regulate their response and the physical features of the environment. Mechanistic models consider species physiology, life-history, and genetic plasticity to predict current or future locations that fall within the tolerance limit of species. Second, correlative models correspond to realized niche because, in general, primarily environmental variables that correspond with where species are located are used to predict distributions where a species is likely to be present. Correlative models that represent realized niche are most popular because mechanistic information is often difficult or time consuming to obtain for certain species.

However, there is a debate among ecologists as to what type of niche the models truly represent. It is argued that niche models approximate a species's fundamental niche (Soberon & Peterson, 2005), while others demonstrate that niche models offer a spatial, or geographical, representation of the realized niche (e.g, Austin *et al.,* 1990; Guisan & Zimmermann, 2000;

Pearson & Dawson, 2003). Araujo and Guisan (2006) argue that the distinction between fundamental and realized niche is not useful in niche modelling, but that it is important to accept that any explanation of the niche is not a complete description of the abiotic and biotic factors permitting species to inhabit certain environmental space.

SDMs have been developed to predict geographic areas that have suitable habitat for species to survive in, and are therefore useful for planning and management of species (Kearney *et al.,* 2010). The use of SDMs to investigate the potential impact of climate change on a species' distribution is based on the assumption that the current environmental niche inhabited by a species can be used to anticipate a distributional response to changes in environmental conditions (Stockwell & Peterson, 2002). The models use the associations between environmental and known species occurrences to identify areas that have suitable conditions where populations can be maintained (Araujo *et al.,* 2006). In addition, SDMs have been widely used to make decisions about habitat choices for species re-introduction (Graham *et al.,* 2004; Hernandez *et al.,* 2006; Adams-Hosking *et al.,* 2012, Mwambo & Cabral, 2014), to test evolutionary hypotheses (Strubbe *et al.,* 2013; Saupe et al., 2014; Kolanowska & Szlachetko, 2014), and to predict potential range shifts due to predicted climate change models (Evangelista *et al.,* 2013; Lotter & Maitre, 2014). For exa mple, in Haiti, coffee farmers were advised to diversify crop varieties because available land in some areas was thought to not be suitable for coffee plantations following the predicted climate change (Eitzinger *et al*., 2011). The authors also suggested that different crop species might respond differently to the predicted climate change, where some crops experience habitat gain while others suffer habitat loss (Eitzinger *et al*., 2011).

Climate change will likely result in new or different environments and ecosystems, which presents scientists with serious challenges in predicting the impact of climate change on ecosystems (Fitzpatrick & Hangrove, 2009). It therefore becomes necessary that the most robust methods be used in order to predict impacts on species in order to develop proper management options. There are many different methods that have been developed to model a given species-distribution [e.g., Bioclim (Busby, 1991), Domain (Carpenter *et al*., 1993), GARP (Stockwell & Peters, 1999), and Maxent (Phillips *et al.*, 2006)]. Previous work compared the performance of the different methods to identify the most statistically robust model for different sampling scenarios (Hernandez *et al*., 2006). The study showed that model accuracy increased with large sample sizes for all modeling methods, as expected. However, Maxent's performance was better than the other methods tested because it performed well and remained fairly stable in both predictive accuracy and the total area predicted across all sample size categories (Hernandez *et al*., 2006). A possible reason for Maxent's success can be attributed to the regularization parameter that counteracts over-fitting models when using only a few species' localities (Phillips *et al*., 2008). Maxent allows the user to include just presence-

only data, with a defined set of environmental variables that are associated with a chosen species (Phillips *et al*., 2006; Merow *et al*., 2013). Maxent produces three different outputs for its predictions: raw, cumulative and logistic. For studies in assessing impacts of climate change on species distribution logistic output is preferred as it is easier to conceptualize probability of presence. Once models are generated, the area under the receiver-operator curve (AUC) is used to determine the predictive accuracy of the model. Values ranges from zero to one, where 1 indicates perfect fit while less than 0.5 indicates that the model does not perform better than random (Baldwin, 2009). Ensuring model accuracy is important as these models can be informative about how species might respond to climate change.

There have been a number of studies that have used Maxent to predict the effect of climate change on species (e.g., Graham *et al.,* 2011; Khanum *et al.,* 2013). These studies have indicated that there will be a change in a species' distribution in response to climate change. For instance, in Pakistan, medicinal plants, such as *Pentatropis spiralis* (Aakari bel)*,* may exhibit increases in habitat size, whereas others like *Tylophora hirsuta* (Indian ipecac) and *Vincetoxicum arnothianum* (Wight) will lose a significant portion of their current habitat (Khanum *et al*., 2013). Here in South Africa, recent work suggests that *Aspalathus linearis* (Rooibos tea) will undergo a dramatic range contraction under the pessimistic emission scenario (A2). This A2 scenario reflects high-energy requirements resulting in an increase of greenhouse gases in the atmosphere that could raise the mean global temperature (Lotter & Maitre, 2014). In Ethiopia, a study that modeled important cereal crops, namely maize, sorghum, teff, and barley distribution, using Maxent indicated that there would be geographic shifts as some areas will experience a decrease in land suitability for cereal crops under future climate changes (Evangelista *et al.,* 2013). Collectively, these studies show that different crops may respond differently to climate change and more information is necessary to better understand how individual species will respond to climate change.

Understanding how agricultural crops will respond to climate change ensures that mitigation measures are developed in advance and assist in developing policies to ensure that the threat to food security is reduced. Khanum *et al.* (2013) suggest that modeling species' distributions can assist in making recommendations for relevant authorities to deal with potential climate change. For instance, if the model predicts that a particular land area will not be suitable for a certain plant species, *ex-situ* measures can be used to preserve plant species. The close link between agriculture and climate makes it necessary to study the impacts of climate change to better understand how crops will respond and help to advise farmers or relevant stakeholders on how to alter their agricultural practices (Lotter & Maitre, 2014).

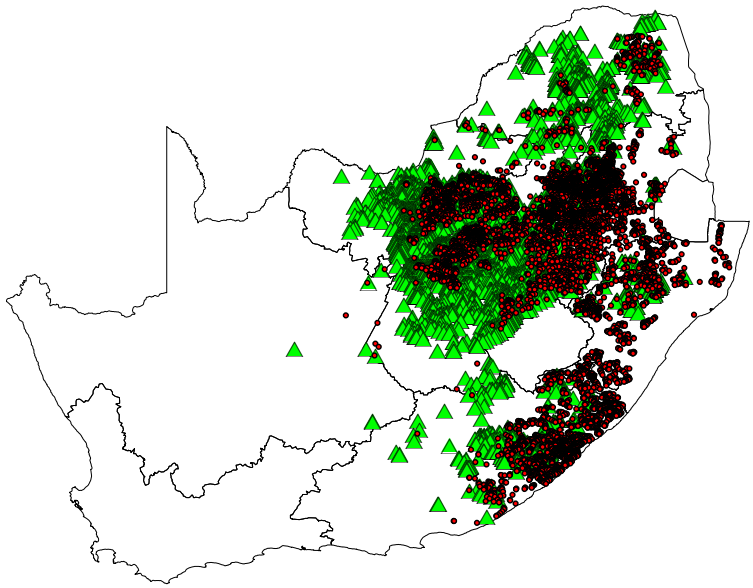


Figure 1. Map of low yield (green) and high yield (black) distribution of maize under current climate plotted from data kindly supplied by B. Bradley (University of Massachusetts, Amherst).

Zea mays (maize) is the world's most widely cultivated crop, and in South Africa is mainly farmed in the Highveld region, which constitutes the whole of Gauteng, almost the whole of the Free State, portions of the Northern Cape, Mpumalanga, North West and Limpopo. The Highveld is characterized as a summer rainfall area, and as a result receives the majority of its precipitation between the months of October and March. The monthly means of temperatures range from 28°C to 30°C in the western part of the region and 25°C to 30°C in the eastern part annually (Walker & Schulze, 2008). Maize is a C_4 plant, which allows maize to tolerate high temperatures (Jones & Thornton, 2003; Walker & Schulze, 2008). It also requires a minimum habitat temperature for germination of 10°C and a maximum temperature less than 32°C. In the Highveld region, particularly in the drier western parts, rainfall is the major limiting factor to crop development. If climate change leads to an increase in the possibility of drought, the area might no longer be suitable for maize development, as rainfall of 500 mm to 750 mm or more is needed for maize development (du Plessis, 2003). Even though the majority of maize produced is grown in commercial farms with irrigation, due to the scarcity of water in South Africa, a significant percentage of maize crops depend on rainfall. It is well established that crop growth is largely dependent on climatic variables, such as temperature and precipitation. Agricultural crops tend to demonstrate negative responses to unfavourable weather events, which have an impact on agricultural productivity and food production. Maize plants are hardy and are able to survive harsh conditions, but drier or warmer climate and lower precipitation tend to have negative effect on maize yield. It becomes necessary to assess how climate change will influence maize's current geographic distribution.

Studies have shown that a reduction in crop production is likely to occur under predicted climate changes (Mendelsohn, 2009; Eitzinger *et al*., 2011). Jones and Thornton (2003) investigated how climate change will affect maize production in Africa and Latin America using a process based model to determine yield. Sites that were modeled had a significant number of rainfed maize-farms, instead of irrigated farms. The results showed an overall reduction of maize production by 10% under future climate change. However, the model indicates that some areas will experience an increase in maize yields; one particular area is in the Ethiopian highlands surrounding Addis Ababa (Jones & Thornton, 2003). In the central part of Chile, like South Africa, maize is cultivated during the spring-summer season (October to March). Impacts of climate change on maize production under irrigated conditions were assessed using a crop simulation model, which simulates the growth and reproduction of a crop in relation to environmental conditions and management practices (Meza *et al.,* 2008). Their data showed that maize has the potential to experience 10% to 30% of yield reduction in central Chile, depending on the severity of the changing climate (Meza *et al.,* 2008). In another study, Walker and Schulze (2008) investigated the sustainability of maize production in the Highveld region in South Africa. Their study indicated that climatic changes could have major negative impacts on some parts of the Highveld region as some areas will experience reduction in maize yields as temperatures increases and there is a decline in rainfall. Abraha and Savage (2006) used a crop simulation model to investigate the effect of climate change on maize yield at the agricultural research station, Cedara, in the midlands of KwaZulu-Natal, South Africa, a summer rainfall location. Their results indicated that maize yield reduction was influenced more by an increase in temperatures than reduction in rainfall. Cedara is located in the eastern seaboard of South Africa it currently has a fairly good rainfall. Climate change predictions indicate that the eastern part of South Africa will experience adequate or an increase in precipitation (Abraha & Savage, 2006).

The Ricardian approach (Mendelson *et al.,* 1994) assesses the economic impact of climate change on agricultural crops. This method relates climate variation or change with net revenues of crop species. The method also assumes that farmers are economically prudent and that they will pursue farming activities that give them the highest returns on any given piece of land (Zinyegere *et al.,* 2013). Gbetibouo and Hassan (2005) used the Ricardian approach to measure impact of climate change on seven field crops in South Africa (viz. maize, wheat, sorghum, sugarcane, groundnut, sunflower and soybean), against predicted climate changes. Their findings indicated that maize is sensitive to marginal changes in temperature as well as precipitation and they predicted that in some regions, maize will no longer be economically viable to cultivate due to increases in temperature and reduction in rainfall (Gbetibouo & Hassan, 2005).

Although models that are used to predict crop yields, production, and sustainability in agriculture are useful to assess the economic responses to the changing climate, these models cannot be used to predict the changes in the geographic distribution of suitable climatic habitats under future climatic conditions. Therefore, SDMs can be helpful to predict how climate change will influence changes in the geographic areas where maize can be successfully cultivated (Liu *et al.,* 2011). For example, Ureta *et al.* (2012) used SDM to determine suitable habitat for cultivating maize under current and future climatic conditions in Mexico. This was based on the realization that 85% of maize is produced by small-scale farms, which are primarily dependent on rainfall. This dependency makes farming more vulnerable to changing climatic conditions. Their findings indicated that under scenarios of high emission there might be significant reductions in potential distribution areas for maize farming. HE and Zhou (2012) used Maxent to predict suitable areas for cultivation of maize in China against the effects of climate change. The model predicted changes in geographic distributions and indicated that several climate variables (i.e., annual precipitation, warmest month average temperature and frost free period) are responsible for making an area suitable or unsuitable for growing maize. Evangelista *et al.* (2013), with the realization that the majority of subsistence food produced in Ethiopia comes from rain-fed agricultural systems resulting in a dependency on climate, used Maxent to assess the impact of climate change on cereal crops, with maize being one of the crops selected as it accounts for 36% of the grain production. Climate scenarios ranging from conservative and pessimistic scenarios representing low emission and high emission as compared to RCPs indicated decrease in suitable area for maize. The following two bioclimatic variables showed highest permutation importance for model distribution: precipitation of the wettest quarter and precipitation of the driest month. Bradley *et al.* (2012) investigated how changes in the distribution of lands suitable for agriculture due to climate change may impact on protected areas as some crops may gain or lose suitability in the current geographic distribution, as a result Maxent was applied on wheat and maize in South Africa. The study showed that under future climate changes both wheat and maize experience a shift in land distribution and these shifts could result in exploitation of protected areas for cultivating those crops (Bradley *et al.,* 2012).

Correlative, mechanistic, and hybrid niche models were used to predict the productivity and impact of global climate change on maize in Brazil (Nabout *et al.,* 2012). The hybrid approach was adopted because there are different views about the effectiveness of correlative and mechanistic niche model approach. The hybrid niche model operates by using mechanistic model as another predictor in the correlative model. The results indicated that correlative and hybrid models output were very similar, while mechanistic model presented very different outcomes from the other two models. The correlative model demonstrated that in Brazil there will be a little change in terms of land suitability of cultivating maize when comparing current climatic and future climate scenarios (Nabout *et al.,* 2012). These results contrast findings from

Assad *et al.* (2008) study in Brazil, which found a greater reduction in potential geographic distribution of maize under future climate change. This is attributed to use of different projection techniques as well as set of predictors (Nabout *et al.,* 2012). Sometimes it becomes necessary to include empirical and mechanical models comparison so as to provide a fuller picture of crop climate uncertainties (Estes *et al.,* 2013). In another study in South Africa by Estes *et al.* (2013) a comparison was done between a mechanistic and a correlative model (Maxent) to test differences in suitability habitat as well as productivity in South Africa. This study was undertaken in response to the criticism that empirical models often ignore biotic interactions (Boulangeat *et al.,* 2012). Estes *et al.* (2013) showed that correlative models have the ability to achieve the same or better accuracy as mechanistic models in projecting species habitat suitability. In another study Kearney *et al.* (2010) demonstrated that correlative (Maxent) and mechanistic models can provide similar, accurate predictions on current and predicted climate change impact on species distribution. Their conclusion was that correlative-only predictions are justifiable.

SDMs are able to indicate how distribution of species will differ from both current and future climate scenarios. However, statistical tests are useful to interpret the significance of how niches differ. Statistical tests of niche identity and niche similarity are often performed by ecologists when testing for differences between two climatic habitats in different time slices; the hypothesis for niche identity predicts that there will be no significant differences between current and future habitat after the effects of climate change (Warren et al., 2008; Broennimann *et al.,* 2012). On the other hand, niche similarity evaluates whether the climatic niche occupied in one area or time period is more similar to the one occupied in the other area than climatic niche assembled by random from both areas. The niche similarity test is able to determine the differences between current and predicted climatic habitats of species are climatically based or simply due to chance (Warren *et al.,* 2008; Broennimann *et al.,* 2012). These tests are able to determine whether a species occupies identical or shows significant difference in climatic niche, and whether these differences are as a result of the environmental feature space under current and predicted climate change (Zhu *et al.,* 2013). These tests will assist in determining whether maize would experience a climate niche shift or not. This will assist in the development of adequate mitigation and adaptation measures for maize.

Chapter 2

Introduction

For the past decade, scientists have extensively investigated change in climate as a result of anthropogenic impacts (Botkin & Keller, 2012). There is evidence that the increased level of carbon dioxide as well as other gases is predicted to accelerate global warming and other significant climatic changes over the next century (Mendelsohn *et al.,* 1994). Due to the fact that climatic conditions play a significant role in influencing the distribution of plant species and vegetation types across the world (Pearson & Dawson, 2003), it is plausible to expect that climate change will have an impact on plant distributions (Alkemade *et al.,* 2002). Recent analyses indicate that climate change already affects species and ecosystems and will continue to do so (Thomas *et al.,* 2004; Chen *et al.,* 2011; Araujo *et al.,* 2013). There are already well-studied changes in the marine, freshwater and terrestrial groups, mainly in Northern hemisphere groups. These changes include earlier timing of spring events, such as leaf unfolding, egg laying, migration, as well as pole-ward and upward shifts in species' ranges. The changes are in line with what is expected under global warming (Parmesan, 2006; Yates *et al.,* 2010).

According to Bryan *et al.* (2009), the Intergovernmental Panel on Climate Change (IPCC) predicts that Sub-Saharan countries will experience warming that is greater than the global average, and in some parts of the Sub-Saharan regions rainfall will decline. Southern Africa is regarded as a region susceptible to climate related risks because of the region's inadequate mitigation and adaptation capacity (IPCC, 2007). Over 60% of the region's livelihood is dependent on agriculture, which is mostly practised under rain-fed conditions, making crop production in southern Africa to be particularly prone to climate change and variability. In southern Africa, projected climates have potentially negative implications for crop production and livelihoods; this is because maize crops are mainly located in the dry sub-humid and semi-arid zones. Already these regions are currently experiencing high summer temperatures with a significant portion also experiencing below 1000 mm of annual rainfall. Predictions of temperature increases or rainfall decline could result into widespread crop failure (Zinyegere *et al.,* 2013). In South Africa, the prediction is that the mean air temperature will increase by 2°C over the next century (SAWS, 2014). The higher temperatures will lead to changes in the timing, frequency, and the intensity of rainfall events. Significant changes in rainfall variability are expected to occur throughout the whole of South Africa, which will result in changes in patterns of floods and droughts. Increased rainfall is projected for the Eastern Cape and KwaZulu-Natal and decreased rainfall for the Western Cape, Northern Cape, central interior (North-West, Free State, Gauteng, and Mpumalanga) and Limpopo provinces. These expected climate changes pose threats to conservation management as well as to agricultural crop species (Cahill *et al.,* 2012). In South Africa, only 14% of the country land is potentially arable, with one fifth of the

land having high agricultural potential. Climate plays a significant role in determining the potential agricultural activities; as a result unfavorable climatic conditions would put the country of losing what is left of the arable land (FAO, 2007). The United Nations Framework Convention on Climate Change has identified agriculture as particularly vulnerable to climate change (UNICEF, 2011). Although there have been technological advances in agriculture, such as much improved crop varieties and irrigation systems that result in an increased yield of crop species, weather and climate still play a significant role in determining crop growth and yield. Consequently, it is important to take into consideration the potential impacts of climate change on agricultural crop species, to assist in developing management plans that will mitigate the negative impacts of future climate changes (Parry *et al.,* 1999). There are a number of methods that are available for predicting the potential impacts of climate change, with each method having its own weaknesses and strengths (Sutherland 2006; Yates *et al.,* 2010). Maxent was used for this study to investigate the potential impacts of climate change on maize distribution in South Africa. Having an understanding on how maize will respond to future climate is important for both agricultural and economic reasons. Majority of South African population consume maize as a staple food and it is also used for animal feed. The country also exports maize to countries such as Japan, Taiwan, China, Swaziland, Namibia and Lesotho (DAFF, 2008). The suitability of maize agro-ecosystems under future climate predictions is of vital importance for the nation`s food security (Conway, 1987; Walker & Schulze, 2008). In South Africa, work on climate change impacts on maize using various methods has indicated that production of maize is under threat (Walker & Schulze, 2008; Bradley *et al.,* 2012; Estes *et al.,* 2013). Although much research has been done to determine the potential impact of climate change on agricultural crop species, there are few studies that focus on agricultural crop species using SDMs in South Africa. As a result this project adopted the use of SDMs to study the impact of climate change on maize distribution in South Africa. To guarantee sustainability of maize production in South Africa under the conditions of future climate change, it becomes necessary to understand the effects of climate change on maize production and to identify areas where maize can be cultivated in the future. The use of SDMs, as well as the ordination approach to determine statistically whether there are significant changes between current and predicted climates, will ensure that climatic factors affecting maize cultivation in South Africa are identified as well as potential suitable areas for maize cultivation. Knowing how maize will respond to climate change will assist in developing adequate adaptation measures to promote future food security in South Africa as maize is a staple crop that the majority of South African population depends on.

Aims and Objectives

The aim of this study was to compare the present distributions of maize in South Africa to potential distributions under RCP2.6 (low emission) and RCP8.5 (high emission).

The aim was met by the following objectives:

1. To determine potential distribution of maize in South Africa under current and predicted climate scenarios using Maxent.
2. To determine how the environmental factors change between current and predicted climatic habitat distributions and their likely influence on maize distributions in South Africa.
3. To statistically compare present and future distributions of maize using multivariate analysis.

Questions

1) What are the environmental factors that contribute most to distribution of cultivated maize in South Africa?

2) How do the climates of geographic regions for maize fields change under different climate change scenarios?

3) Will the present climate habitat of maize be suitable for maize as climate changes?

Methods

Study area

Maize is one of the main crops cultivated in South Africa (Walker & Schulze, 2008). It is a summer crop, grown in semiarid regions of the country, it highly susceptible to changes in temperature and precipitation; as a result climate change has the potential to affect maize production as maize requires 500 to 1000 mm of rainfall in the October to March growing season in order to grow successfully (Durand, 2006; Benhin, 2006; Akpalu *et al.,* 2008). Maize is predominantly cultivated in the Highveld region of South Africa. The Highveld region (Figure 2) is the part of the South African inland plateau and has an altitude above approximately 1500 m.a.s.l. It constitutes almost the whole of the Free State, Gauteng, portions of the Northern Cape, Eastern Cape, Limpopo, and Mpumalanga. The soils in the region are generally a sandy clay loam texture, with thickness ranging from 400 mm to 1200 mm, although clay soils are mostly found in parts of Gauteng and Mpumalanga. The soils in the region are generally considered as nutrient poor as they have a sandstone origin (Walker & Schulze, 2008).

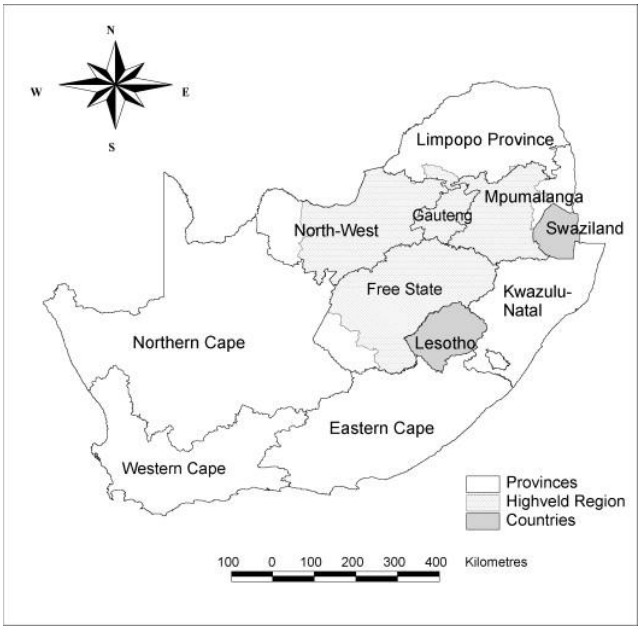


Figure 2. Highveld region (shaded light grey) where maize is predominantly grown (source: du Toit *et al*., 2002).

Data sources

Presence data of maize farm fields were obtained from Dr. B. Bradley, University of Massachusetts (2014, pers. comm.) The data points were originally compiled from the online Producer Independent Crop Estimate System (PICES) database of land use and agricultural areas throughout South Africa. Data of areas include both subsistence and commercial farms; as a result our datasets have both maize high-producing areas (N = 10291 occurrence points) as well as maize low-producing areas (N = 9925 occurrence points). The high yield-yield occurs mainly in commercial farms and this is attributed to better management practices as well as aid of mechanization and have been used in previous studies (e.g., Bradley *et al*., 2012 & Estes *et al*., 2013). These data are at a 1 km^2 (30-arc second) resolution and cover areas of SA where maize has been grown, It is worth mentioning that the datasets do not indicate type of cultivars of maize. ArcGIS 10.2.2 was used to transform the spatial areas of maize crop species into geographic coordinates for Maxent use (Kumar, 2012; Khanum *et al.,* 2013). From the field layers, points were extracted using ArcGIS in order to associate necessary spatial areas with climate data (Figure 2).

Environmental variables

For this research, a climate-only approach was adopted in order to address the overall goal of assessing the impacts of climate change on maize suitability in our study area. Elith and Leathwick (2009) noted that most SDM studies use many candidate predictors, for instance the use of all 19 bioclimatic variables to predict distribution (e.g. Kumar, 2012; Evangelista *et al.,*

2013; Khanum *et al.,* 2013). The use of many predictors is often motivated by the belief that the model will identify predictors that are important (Elith & Leathwick, 2009). For the preliminary analyses for this study, all 19 bioclimatic variables were used and this resulted in reduced predictive accuracy of the model as the AUC value was just above 6.5. Ward (2003) indicates that informative modeling should be based on the correct climatic variables that play a role in the biology of species. Bradley *et al*. (2012) demonstrated that climatic variables that are key to maize survival are growing season precipitation, growing season maximum temperature, and growing season minimum temperature. For this study the following five bioclimatic variables were used to correspond to those identified by Bradley *et al.* (2013): precipitation of the warmest quarter (Bio18), Maximum temperature of the warmest month (Bio5), annual precipitation (Bio12), precipitation of the wettest month (Bio13) and precipitation of the wettest quarter (Bio16). Climate data were downloaded from the freely available WorldClim database ((Hijmans *et al*., 2006; www.worldclim.org). Climatic variables were downloaded at ~1 km^2 grids (30 arc-second resolution). The WorldClim database uses altitude, temperature, and precipitation to calculate monthly, quarterly, and annual climate indices to indicate seasonality and extremes (Hijmans *et al.,* 2006).

WorldClim also provides a dataset that is useful to model future predicted climate variables. Future climate projections of the five bioclimatic variables were downloaded from the WorldClim database. I used the climate projections of the HadGEM2ES model to project climatic habitats for maize under two different emission scenarios relative concentration pathways (RCP); RCP2.6 predicts low carbon dioxide concentrations and low carbon emissions worldwide, and RCP8.5 predicts increasing CO_2 concentrations and high carbon emissions worldwide for 2050. These newer scenarios are updated from previous climate predictive scenarios of the IPCC and allow for a range of climate predictions to be tested under a variety of socioeconomic factors. For this project, RCP2.6 and RCP8.5 (Figure 3) scenarios were used to model the “best possible” (RCP2.6) and “worst-case” scenarios (RCP8.5) of emissions and carbon dioxide levels using the HadGEM2ES model for 2050.

Modelling assumptions

To produce SDMs of maize species in both low producing and high producing areas in South Africa, a number of assumptions were made. Biotic interactions with other species such as competitors (invasive plants) and parasites were not considered even though interactions with other species can play a role in determining a species’ distribution (Pearson & Dawson, 2003). The ability of maize to adapt to predicted climate change because it is a drought- resistant cultivar was not considered. This is because the data provided did not specifically outline the differences between possible cultivars, merely outlined if the locality was a ‘high-yield’ location

or a 'low-yield' location due to previous work (Bradley *et al.,* 2012). It was assumed that maize occurs in areas that are climatically suitable whilst being absent from unsuitable ones in South Africa (Araujo & Pearson, 2005).

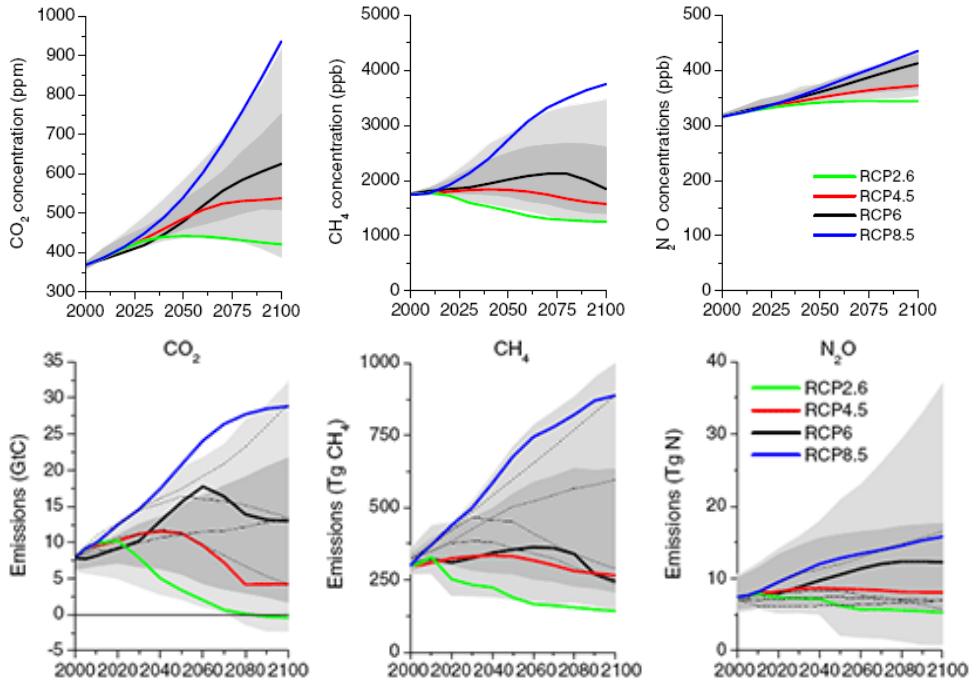


Figure 3. Comparison of four relative concentration pathways (RCPs) and carbon dioxide concentration (1st graph) between 2000 and 2100 and for emissions in gigatons of carbon dioxide (4th graph) (Figure taken from van Vuuren *et al*., 2011).

Data Analyses

The potential distribution of maize in both low producing and high producing areas were modeled using Maxent v.3.3.k (Phillips, 2006; 2008). Maxent is a niche modelling algorithm used to predict the probability of distributions based on the principle of maximum entropy (Phillips *et al.,* 2006). Maxent uses a list of species localities and associated environmental predictors as input. From the identified environmental landscape, Maxent extracts background locations that it contrasts against the presence locations; it starts with a uniform distribution then uses an iterative approach to increase probability value over locations with conditions that are similar to selected samples (Merow *et al.,* 2013). It is important that environmental layers are in ASCII raster format and that they have the same projection system and the same geographic boundary and cell size (Young *et al.,* 2011).

Maxent was selected due to the fact that it performs well when compared to other ecological niche models including those that factor in biotic interactions (Elith *et al.,* 2006; Hernandez *et al.,* 2006). Maxent should produce a reasonable characterization of the spatial distribution of current and future climate conditions required by maize crop species in South Africa (Bradley *et al.,* 2012). Default settings were used in running of the model. Both response curves and jackknife tests were conducted in order to identify which bioclimatic variables influence maize distribution the most. Seventy percent of the occurrences were used for training the models and 30% of occurrences for testing models. Training occurrences are used to build the models, whereas testing occurrence are used to evaluate the ability of the trained model to predict real occurrences (Thompson *et al.,* 2014). Model performance was evaluated using the area under the operating curve (AUC). Models with AUC values over 0.7 are performing well, with over 0.9 being excellent and below 0.5 is regarded no better than random (Hill & Terblance, 2014).

Range shift analyses

In order to evaluate maize species range shifts between current and future predicted climate changes, the current and predicted distribution maps raster were converted into polygons. The sum area of both present and predicted climate habitats were calculated in ArcGIS. A Chi-square test was done to test whether there was a relationship between the range size (in area) of the current climate habitat of maize and the range size (in area) of the predicted climate change habitat. Cramer's test was performed as it is the most popular of the chi-squared based measures as it gives good norming from zero to one irrespective of the table size (Muthoni, 2010). Values close to zero indicate little association while values close to one indicate strong association. High association between current and predicted climate change maps indicate less changes in the distribution of species between two time periods. The analysis for chi-square was done using SAS statistical software.

Niche overlap between current and predicted climate changes (Maize)

Ordination techniques or SDMs can be used to quantify environmental habitat and to assess habitat differences (Broennimann *et al.,* 2012). Both methods use species occurrence records with a given set of environmental predictors to characterize niches (Strubbe *et al.,* 2013). SDMs correlate environmental variables to georeference data of species occurrences. This association results in a niche overlap value to be estimated through the projection of those functions across an environmental landscape (Broennimann *et al.,* 2012). Warren *et al*. (2008) developed an SDM-based method that compares the geographical prediction of occurrences to randomized predictions to quantify niche differences and assess their statistical significance. There are number of ordination methods suggested by Broennimann`s *et al*. (2012). For this project, Principal Component Analysis calibrated on the entire environmental space of the current and predicted climate change including species occurrence (PCA-env) was chosen as it

is considered the ordination method that is able to determine niche overlap without bias. In addition, a statistical ordination method was used to compare predicted present and future climatic niches of maize in South Africa. The ordination method developed by Broennimann *et al.* (2012) uses a multivariate approach based on principal coordinate analyses and involves three steps: 1) calculation of the density of occurrences and environmental factors along environmental axes of multivariate analysis, 2) measurement of niche overlap along the gradients of multivariate analysis, and 3) statistical tests of niche identity and similarity (Warren *et al*., 2008; Broenniman *et al.,* 2012). This ordination technique allows direct comparisons of species climatic niches in environmental space that are independent of geographic area. Using an ordination framework helps to account for biases introduced by spatial resolution; this is achieved by the application of a kernel smoothing approach, which corrects observed occurrence densities for each region with respect to availability of environmental space.

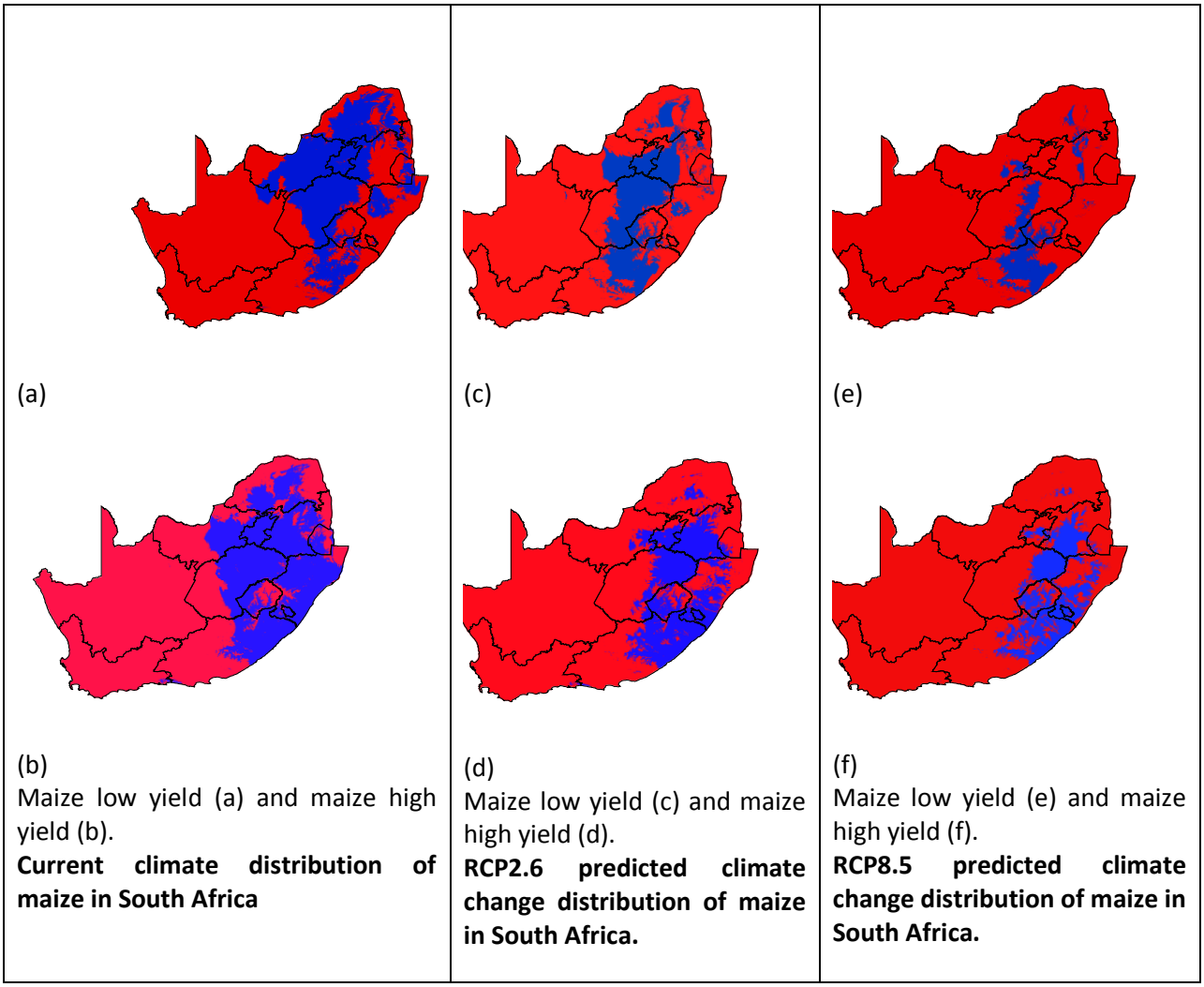
The niche identity test was performed to explore whether climatic niches of maize under current and future predicted climate change are identical in both low producing and high producing areas. A "niche overlap" statistic is calculated, which is based on Schöner's *D* (Schöner, 1970; Warren *et al*., 2008). The metric ranges from zero, which indicates niches are not the same, to one, which signifies that niches completely overlap. In order to test for significance of the overlap value, the climatic niches were then randomized and new, random climatic niches were generated to test for overlap with the actual climatic niche. This randomization was repeated 100 times to generate a null distribution If the observed D value is greater than or less than the range of values that comprise the null distribution, then the hypothesis of niches being identical is rejected (Warren *et al.,* 2008). The test for niche identity is conservative because it only determines if maize species under different climatic conditions are identical in their niche space by using their exact locations and does not take into account the surrounding space (Aguirre-Gutierrez *et al.,* 2014). This niche similarity test also involves the calculation of a null distribution of 100 simulated niche overlap values. It then explores niche overlap of the current climatic niche with a random model based on the background of the predicted climate niche of maize, and then the reciprocal, resulting in two null distributions, one for each climatic niche, to which the actual niche overlap between current and future climate niche is subsequently compared. A statistically higher niche overlap value shows that the niches are more similar than expected by chance. The niche similarity test and niche identity tests were done in R (R Development Core Team, 2010) using a script developed by Broennimann *et al.* (2012).

Results

Models for maize in both low- and high-producing areas under current and predicted climate change performed better than random, AUC values ≥ 0.7. For maize low-producing areas under current climate conditions, the model predicted suitable climate in the Highveld region. Areas that include the upper region of Limpopo province, Kwazulu-Natal and some parts of the Eastern Cape Province also show suitable areas for cultivating maize under current climate conditions from the model (Figure 4a). The variables that made the largest contribution were precipitation of the wettest quarter (Bio18) and annual precipitation (Bio12) contributing 55.6% and 14.9% respectively in determining climate suitability for maize (Table 1). From Jackknife tests of variable importance, Bio18 and Bio16 were the variables with the highest gains, which indicates that Bio18 and Bio16 had the most useful information in making predictions for climate suitability of maize. Bio5 reduced the gain when omitted; this indicates it has useful information. The Maxent prediction for maize low-producing areas under the predicted conservative emission scenario RCP2.6 indicates that western part of Limpopo province as well as the North West, and the western part of the Free State province will experience a loss in climatic suitability of maize. On the other hand, the suitability of maize in the Eastern Cape will increase (Figure 4c). Bio18 and Bio12 were the most important variables in predicting suitability based on the percentage contribution in this scenario (Table 1). Bio18 and Bio16 were the variables with highest gains, while Bio5 reduced the gains of the model when it was not included based on the jackknife test. These results indicate that Bio18, Bio16 and Bio5 had the most useful information in predicting climate suitability for maize. For the pessimistic scenario RCP8.5, predictions show that there is going to be a great loss of climatic suitability for maize low-producing areas in the following provinces: Limpopo, North West, Gauteng, Free State, Kwazulu Natal and Mpumalanga. The Eastern Cape Province shows that it will not suffer huge loss as the area still indicates a significant portion of climate suitability (Figure 4e). Bio18 and Bio16 were the variables that contributed the most to the model prediction (Table 1) and this was confirmed by the jackknife test.

Present climate suitability for maize high- producing areas indicated a similar distribution as for maize in low producing areas; the noticeable exception is that in KwaZulu-Natal there is an increase in climate suitability for maize (Figure 4b). The distribution of maize was strongly influenced by Bio18 and Bio12 based on the percentage contribution (Table 2) and the jackknife test. Bio5 reduced the model gains when omitted this show that it has valuable information in model prediction. A future prediction of climate suitability for maize under RCP2.6 shows a decrease in climate habitat on the western part of the Highveld region as well as in the northern part of Limpopo province. However, the eastern part of the Highveld still shows adequate climate suitability as well as the Eastern Cape and KwaZulu-Natal provinces (Figure 4d). Bio18 and Bio12 had the highest contributions of 48.9% and 35.8% respectively (Table 2),

with the jackknife test showing the same variables as having a significant impact on the Maxent prediction. Finally the Maxent prediction under the pessimistic scenario of high emission (RCP8.5) showed a trend of reduced climatic suitability in almost the entire North West province, and significant loss of climate suitability in the western part of the Free State province, Gauteng and Limpopo province. The eastern part of the Free State shows suitability, as well as the eastern part of Mpumalanga province; KwaZulu Natal shows some areas that are suitable and the Eastern Cape shows reasonable climate suitability for maize cultivation (Figure 4f). Bio18 and Bio16 were variables with the most useful information based on the jackknife test and also these variables contributed highest in the model building (Table 2).



(a)

(b)

Maize low yield (a) and maize high yield (b).

Current climate distribution of maize in South Africa

(c)

(d)

Maize low yield (c) and maize high yield (d).

RCP2.6 predicted climate change distribution of maize in South Africa.

(e)

(f)

Maize low yield (e) and maize high yield (f).

RCP8.5 predicted climate change distribution of maize in South Africa.

Figure 4. Maxent output of maize distribution in both low and high yield geographic locations under current and predicted climate change scenarios comparison.

Table 1. Selected bioclimatic variables for maize low yield contribution to Maxent model under current and predicted climate change scenarios.

Variables	**Current climate**		**RCP2.6 climate**		**RCP8.5 climate**	
	% contribution	Permutation importance	% contribution	Permutation importance	% contribution	Permutation importance
Bio18	55.6	39.6	54	40.9	49.5	35.8
Bio12	14.9	17.3	16.1	18.1	15.3	23.1
Bio16	12.3	21.8	8.1	19.7	18	18.9
Bio5	12.2	16.6	10.4	16.7	10.7	17.1
Bio13	5	4.6	11.4	4.7	6.4	5.1

Table 2. Selected bioclimatic variables for maize high yield on Maxent model under current and predicted climate change scenarios.

Variables	**Current climate**		**RCP2.6 climate**		**RCP8.5 climate**	
	% contribution	Permutation importance	% contribution	Permutation importance	% contribution	Permutation importance
Bio18	49.3	40.1	48.9	41.5	49.5	35.8
Bio12	36	14.3	35.8	13.6	15.3	18.9
Bio16	0.4	8.9	0.4	9.3	18	23.1
Bi05	13.7	22.1	14.3	21.6	10.7	17.1
Bio13	0.5	14.6	0.6	14	6.4	5.1

Maxent output grid under current climate conditions shows that the area of maize high-producing area covers an estimated 2,583,245.646 ha. For the RCP2.6, the area for maize covers 1,938,519.875 ha which is a decrease in land cover, on the other hand the pessimistic RCP8.5 shows an additional decrease as the land cover for maize cultivation is 1, 809, 769.154 ha (Table 3). For maize low-producing areas, Maxent output grid under present climate conditions indicates a land cover of 2,949,635.519 ha as suitable for maize cultivation. The RCP2.6 predicts a decrease in land cover with 2,198,614.077 ha suitable for maize cultivation. The pessimistic RCP8.5 model indicates a further decrease as the land cover is 1, 573,136.383

ha (Table 3). The chi-square test for association between present and predicted climate distribution of maize in both low and high producing areas indicated the Cramer value of 1 (P > 0.05) (Tables 8 and 9), which indicates that there is no difference between climatic maize suitability land cover areas under current and predicted climate change.

Table 3. Change in area of maize suitability under different climates

Climate Scenario	Area (Hectares)	
	Maize area (high yield)	Maize area (low yield)
Current climate	2,583,245.646	2,949,635.519
RCP2.6 climate scenario	1,938,519.876	2,198,614.077
RCP8.5 climate scenario	1,809,769.154	1,573,16.383

Niche overlap results

Maize low-producing areas under current and predicted RCP2.6 climates showed PCA-env loaded with the precipitation variables accounting for 84.23% on axis one. The second axis was loaded with the temperature variables, which and contributed 13.67% of the variation. The environmental space occupied by maize low-producing areas under current and predicted RCP2.6 climate as determined by PCA-env shows that maize climate habitat in RCP2.6 increases in density (Figure 5). Comparisons for maize low-producing areas under current climate conditions and predicted RCP8.5 shows that axis one was loaded with precipitation variables contributing to 83.93%, while the second axis with temperature variable contributed 13.9%. There was also an increase in climate density for maize in the predicted RCP8.5 compared to current climate conditions (Figure 5).

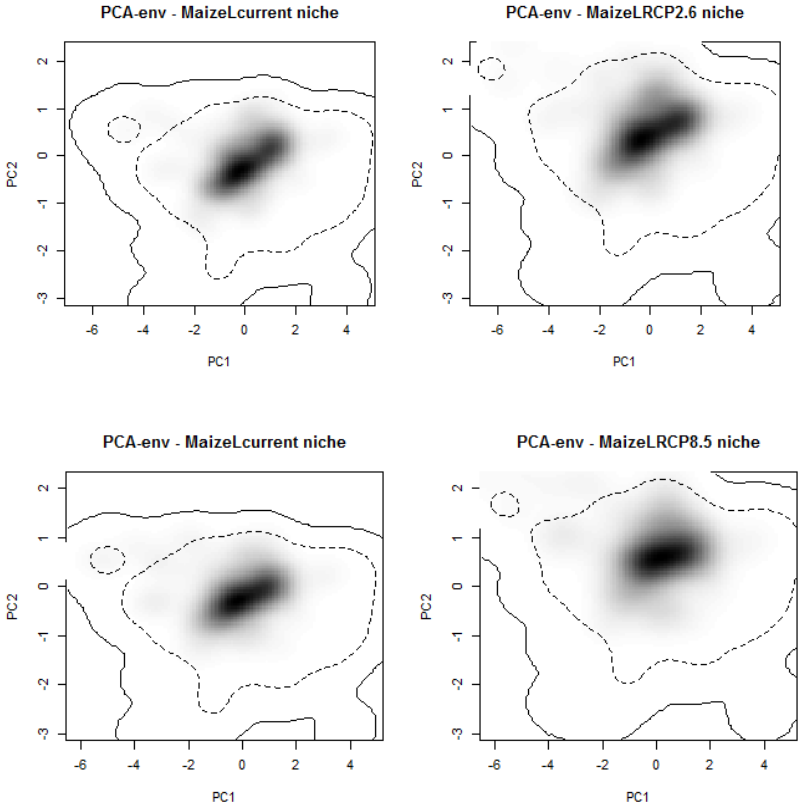


Figure 5. Niche dynamics of maize low-producing areas: under current, RCP2.6, and RCP8.5 predicted climate: environmental space plot represented by the first two axes of principal component analysis summarizing the entire study area. Black shading represents the density of occurrence of maize. The solid and dashes contour line illustrate 100% and 50% of the available environment in the study area.

Value of niche overlap between maize low-producing areas under current and predicted RCP2.6 was 0.522; this indicates a moderate niche overlap of maize in two different climatic conditions. The null hypothesis of niches being identical between the two time slices was rejected (Table 4). For the two time periods the niche similarity tests were more similar than expected by chance, but this was only in one direction. Maize low yield RCP2.6 climate niche was more similar to maize low yield under current climate conditions but not vice versa (Table 5). Value of niche overlap between current and the pessimistic RCP8.5 scenarios produced niche overlap of 0.451 this is moderate niche overlap. The niche identity test hypothesis was rejected, as this demonstrates that climate niches of maize between the two climate conditions are different (Table 4). For the similarity tests, climate niches of maize were not statistically similar in both directions (Table 5).

Table 4. Results from niche identity test that compares niche overlap between maize low-producing areas under current and predicted climate scenarios using PCA-env. Niche overlap values are represented by *D* while the p values indicate the level of significance.

Climate	Current	RCP2.6	RCP8.5
Current	0	P = 1	P = 1
RCP2.5	*D*=0.522	0	-
RCP8.5	*D*=0.451	-	0

Table 5 Table 5. Results from the niche similarity tests for current and predicted climate change niche for maize low-producing in both directions using PCA-env. Niche overlap values are indicated by *D* and p values show the level of significance. Current (a) and predicted (b) climate scenarios are represented in the first column.

Climate conditions		Niche overlap (*D*)	Niche similarity	
a	b		a→b	b→a
Maize current	MaizeRCP2.6	0.522	P=0.356	P=0.0396
	MaizeRCP8.5	0.451	P=0.118	P=0.316

The environmental space occupied by maize high-producing areas under current and predicted RCP2.6 climate conditions shows climate density of maize being more concentrated in the predicted climate change niche (Figure 6). Axis one of the correlation circle was loaded with

precipitation variables that contributed 83.93% of variation in the study area while the temperature variable contributed 13.9% on the second axis. Similarly, comparisons between current and RCP8.5 climate niches produced similar results (Figure 6).

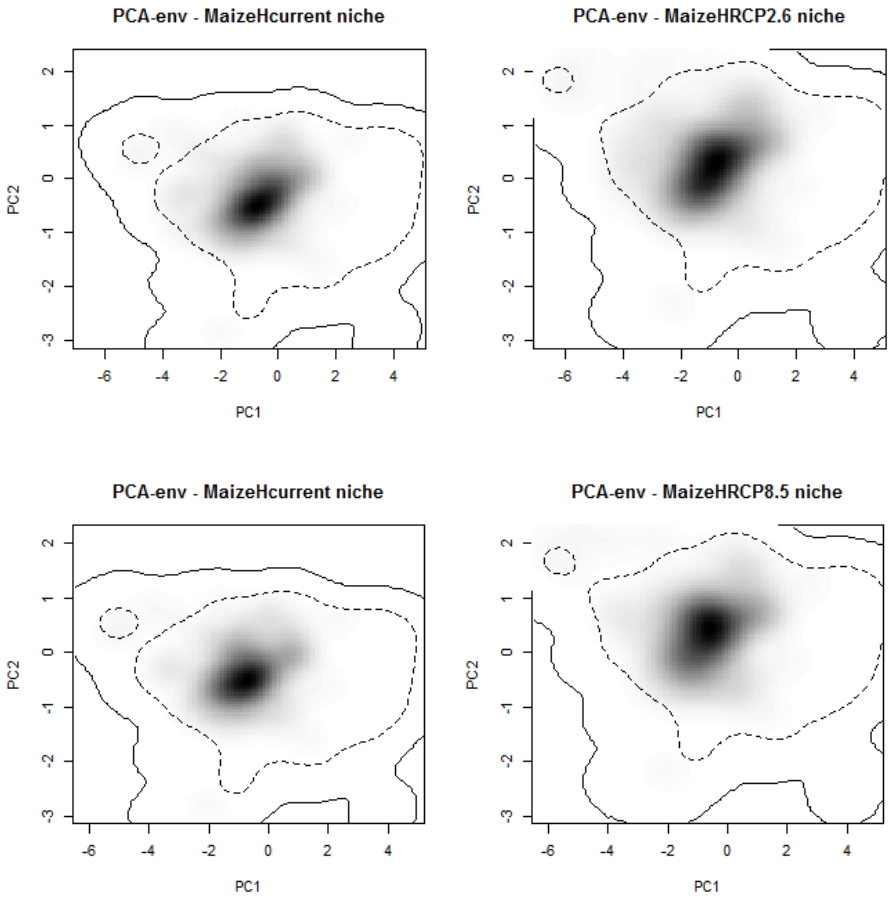


Figure 6. Niche dynamics of maize high-producing areas: under current, RCP2.6, and RCP8.5 predicted climate: environmental space plot represented by the first two axes of principal component analysis summarizing the entire study area. Black shading represents the density of occurrence of maize. The solid and dashes contour lines illustrate 100% and 50% of the available environment in the study area respectively.

Niche overlap value of maize in high-producing areas under present climate conditions against RCP2.6 climate niche is 0.603, which is a relatively high overlap value as it is close to 1 (Rodder & Engler, 2011). The niche identity test hypothesis was rejected, which demonstrates that climate niches of maize between the two climate conditions are different (Table 6). For the similarity tests climate niches of maize were found to be more similar than expected in both directions (Table 7).

The niche overlap value between maize in high-producing areas under current and predicted RCP8.5 was moderate 0.563. The niche identity hypothesis was rejected (Table 6). For the niche similarity tests maize of the current climate niche was more similar to the maize in RCP8.5 climate niche but not vice versa (Table 7).

Table 6. Results from the niche identity test that compares niche overlap between maize high-producing areas under current and predicted climate scenarios using PCA-env. Niche overlap values are represented by *D* while the p values indicate the level of significance.

Climate	Current	RCP2.6	RCP8.5
Current	0	P = 1	P = 1
RCP2.6	*D*=0.603	0	-
RCP8.5	*D*=0.563	-	0

Table 7. Results from the niche similarity tests for current and predicted climate change niche for maize high-producing in both directions using PCA-env. Niche overlap values are indicated by *D* and p values shows the level of significance. . a and b represent current and predicted climate scenarios respectively.

Climate conditions		Niche overlap (*D*)	Niche similarity	
a	b		a→b	b→a
Maize current	MaizeRCP2.6	0.603	P=0.0198	P=0.0396
	MaizeRCP8.5	0.563	P=0.0198	P=0.138

Discussion

For this study, distribution models were produced based on known geographic locations of high-yield and low-yield localities of maize production in South Africa. I used Maxent to predict where maize localities may be found in the context of future climate change. I compared current maize distributions to potential distributions under climate change and found that maize geographic distribution would reduce under projected climate change, more especially in the Highveld region; where 90% of maize is currently cultivated. However, Maxent output model (Figure 4) indicates an increase in area of suitability for maize in the Eastern Cape province, eastern part of the Free State and in Mpumalanga province. Increase in suitability in the eastern regions of South Africa is in line with the expectation from climate models as they predict higher precipitation in the eastern part of the country (Randin *et al.,* 2009). These findings indicate that there are different possibilities for maize distribution in the face of climate change in South Africa.

The results from Maxent and ordination technique have identified precipitation of warmest quarter (Bio18), precipitation of wettest quarter (Bio16), annual precipitation (Bio12), and maximum temperature of warmest month (Bio5) as important variables that constrain maize distribution. These variables are in accordance with what is described in the literature, viz. that precipitation and temperature have a major influence on maize distribution (Schulze & Walker, 2008; Nabout *et al.,* 2012; Ureta *et al.,* 2012). Maxent modeling results show that climate change will have a negative effect on the distribution of maize in the future, for both RCP2.6 and RCP8.5 scenarios. For the RCP2.6 scenario, there is an indication that maize in both low and high yield areas will experience a decline in climatic suitability in the western part of the Highveld region and part of the upper Limpopo province as the conditions are expected to be warmer and drier with climate change (Walker & Schulze, 2008). Currently in the Highveld region, particularly in the drier western parts, rainfall is the major limiting factor to crop development (Walker & Schulze, 2008). Maize high yield, the RCP2.6 scenario indicates a massive loss of suitability also on the western part of the Highveld region with a stable suitability in the Eastern Cape. Total crop area for maize shows that RCP2.6 for maize high-producing areas is less than the current climate conditions. Predictions based on RCP8.5 for maize both low- and high-producing show similar trend, that almost the entire western part of the Highveld region will experience a reduction in maize suitability while in the eastern part there will be areas that will have climate suitable for maize. The Eastern Cape province shows significant areas of climate suitability for maize (Figure 4) under both RCP2.6 and RCP8.5.

Due to the fact that 90% of commercially grown maize in South Africa is produced in the Highveld region, the massive loss of suitability in the area has the potential of threatening the

food security of the country, as well as of neighbouring states that depend on South Africa for maize supply. From the results it is clear that precipitation and temperature variables will have a direct negative effect on the distribution of maize in South Africa. However in order to obtain a clear picture on how climate change will affect maize distribution it becomes necessary to consider biological interactions of maize in its current location. There have been quite a number of studies that have explored the relevance, application and shortcomings of SDMs like Maxent (Guisan *et al.,* 2006; Araujo & Guisan, 2006; Wiens *et al.,* 2009). Shortcomings identified are that biotic interactions are mostly ignored and that there is an assumption that species distribution is mainly influenced by climatic variables (Pearson & Dawson, 2006; Guisan & Thuiller, 2005; Kearney, 2006; Araujo & Guisan, 2006). Pearson and Dawson (2003) noted that the complexity of the natural system presents fundamental limits to predictive modelling. Nevertheless they also observed that the SDMs approach can give a meaningful approximation as to the potential impact of climate change on the ecosystem. It therefore becomes necessary for the study findings to be considered as possible future scenarios that relate to maize distribution in South Africa against climate change. The results of this study give detailed quantitative predictions through time and space of what could happen as a result of climate change on maize geographic distribution in South Africa. Overall the results show that maize is vulnerable to climate change because under both 'conservative and pessimistic' climate scenario, maize will experience a considerable range shift from its current geographic location as the predicted climates favour the eastern part of the country, mainly the Eastern Cape province. Understanding the potential distribution as well as threats faced by maize in the country makes it necessary to come with mitigation measures. One measure that could be used to ease the loss of climatic suitability is to plant maize in areas where climate is going to be suitable. The results from the study indicate that the Eastern Cape province will have adequate climate suitability for maize under both RCP2.6 and RCP8.5. In order to mitigate against reduce climate suitability in the Highveld region It might be necessary to cultivate maize in the Eastern Cape province. Eastern Cape is one of the least developed areas of the country; it has about 15% of the South African population but contributes only 7.5% to South Africa Gross Domestic Product (ECNGOC, 2014). The shift in climate suitability of maize has the potential of providing positive impacts such as job creation, improved infrastructure such as roads to accommodate commercial farming of maize. The shift in climate suitability for maize in the province can also have negative impacts more especially on conservation. The Eastern Cape has a quite a number of protected areas that might be threaten by increase in climate suitability for maize as this areas can be converted into agro-ecosystem as a response measure to counter loss of climate suitability of maize in the Highveld region (Bradley *et al.,* 2012). On the other hand, reduce climate suitability for maize may have a positive impact on conservation as farmers may abandon the land as it becomes economically less viable. This makes it possible to use the land

for conservation management which can only take place when areas affected are able to retain their key species in the face of climate change (Pence *et al.,* 2003; Bradley *et al.,* 2012).

The use of an ordination framework for this study provides the possibility of comparing current climate niche and predicted climate niche overlap of maize. This method was used in order to determine whether maize will have the ability to occupy different parts of its niche in the projected climate. The moderate to high niche overlap between current climate niche and predicted climate niches indicates that niches are experiencing the same environmental constraints in the environmental space. The niche identity hypothesis was consistently rejected signaling that climate niches of current and predicted climate niches of maize are not identical. Niche similarity tests showed an evidence of niche conservatism when comparing maize low yield in RCP2.6 niche and current conditions, as niches were more similar to each other than random expectations predict, however there was a difference in reciprocal test as niches were not more similar than random (P=0.35). Niche similarity tests between maize low yield current and RCP8.5 niche produced non-significant results, leading to inability to make a conclusion about the similarities between niches in the two time periods. For maize high yield, the niche overlap was found to be high between current and predicted climate scenarios. Niche similarity tests showed that niches between current and RCP2.6 are more similar than random, significant similarities can be explained as the possibility of RCP2.6 having the climatic conditions that maize can tolerate. Under the high emission scenario of RCP8.5, current maize niche was more similar than expected with the predicted niche but the reciprocal test indicated the opposite. The ordination method framework indicated that maize has the ability to occupy both current and predicted climate change scenarios' niches even though the niches were proven to be different. Similarity tests showed non-significant results in some cases meaning one cannot conclude whether the niches are similar or different, while in some cases findings suggested that maize niches are more similar than random between the current and predicted climate change niche. Although, the results are not conclusive a pattern of maize niche being adapted to different environmental conditions is shown.

Information how maize will respond to climate change will ensure that adequate mitigation measures are designed. Enough care should be taken to ensure that adaptive measures that are proposed in ensuring maize sustainability to counter climate change do not add stressors on the receiving environment. For example, in order to counter dry conditions in some parts of the Highveld region farmers may choose to use irrigation as well as fertilizers, but these could result in impacting negatively on the quantity and quality of freshwater ecosystem in the area. According to Bradley *et al.* (2012), loss of climate suitability of maize and gain in some geographic locations may pose conservation threats as people may seek additional farmland where certain species may lose their habitat as the area is converted into farming areas.

Conclusion

Results obtained from the study indicate that Maxent can be used to predict the potential distribution of maize in South Africa against climate change. Model results show that climate suitability in the Highveld region, an area where 90% of South Africa's maize is produced, is going to experience a decrease in suitability due to climate change. From this study, bioclimatic variables that influence the distribution of maize the most were precipitation of the warmest quarter (Bio18), annual precipitation (Bio12), and maximum temperature of the warmest month (Bio5). The Eastern Cape province shows signs of increased and stable suitability for maize growth/production under both RCP2.6 and RCP8.5 predicted climate change scenarios. Notably, the future distribution of maize under predicted climate change has the potential of making ecosystems vulnerable. Increases in climatic suitability in the Eastern Cape might put protected areas under threat when the need arise to convert those areas into agricultural land (Bradley *et al.,* 2013). Statistical tests for maize, niche identity using the PCA-env ordination method indicated that maize niches under current and predicted climate change were different. However, the results for niche similarity more often showed that niches are statistically more similar between the two time slices, while in some instances results were inconclusive as non-significant results were obtained. Observed similarities of maize under different time periods suggest that the two time periods have similar bioclimatic constraints, while non-significant results indicate that we cannot really tell how much the niches differ using these broad climatic variables.

Having the knowledge on how the distribution of maize cultivation in South Africa is likely to change in geographical and environmental space over time is important as this will help in developing mitigation measures. Findings from Maxent shows that maize niche in South Africa will be negatively affected by climate change where it is currently cultivated. On the other hand, the ordination technique suggests that climate change will have a little effect on maize climate niche. In the absence of better projections on how climate will impact on maize distribution in South Africa, farmers and decision-makers are faced with the possibility of undermining potential threats that maize face as a result of climate change.

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Appendices

Table 8. The chi-square procedure for maize high yield under predicted climate scenarios .

Statistics for Table of Climate by MaizeH(ha)

Statistic	DF	Value	Prob
Chi-Square	4	6.0000	0.1991
Likelihood Ratio Chi-Square	4	6.5917	0.1591
Mantel-Haenszel Chi-Square	1	1.7417	0.1869
Phi Coefficient		1.4142	
Contingency Coefficient		0.8165	
Cramer's V		1.0000	

WARNING: 100% of the cells have expected counts less than 5. (Asymptotic) Chi-Square may not be a valid test.

Table 9. The Freq procedure for maize low yield under predicted climate scenarios

Statistics for Table of Climate by MaizeL(ha)

Statistic	DF	Value	Prob
Chi-Square	4	6.0000	0.1991
Likelihood Ratio Chi-Square	4	6.5917	0.1591
Mantel-Haenszel Chi-Square	1	0.4118	0.5211
Phi Coefficient		1.4142	
Contingency Coefficient		0.8165	
Cramer's V		1.0000	

WARNING: 100% of the cells have expected counts less than 5. (Asymptotic) Chi-Square may not be a valid test.