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

Tatenda Lysias Magodora

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Corresponding author: tmagodora1@gmail.com

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Abstract: The agricultural sector has remained under threat from climate change despite significant efforts to combat this problem. There is evidence of existing climate change impacts on maize production in South Africa. No meta-analysis was done to compile the impacts of climate change on maize production for economic analysis in the South African context. This study therefore investigates the impacts of global warming on maize production in South Africa using a meta-analysis (for physical impacts) and the Ricardian analysis (for economic impacts). The meta-analysis makes 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 per cent, owing to temperature increase of about 20°C to be realized between 2081 and 2100. The Ricardian analysis makes use of time series data for the period from 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 per cent of revenue, owing to plus 20°C of warming. Given these outcomes, the study suggests the adoption of heat resistant maize varieties and 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.

Key words: climate change, maize production, meta-analysis, Ricardian analysis, bootstrapping, temperature, rainfall

JEL classification: Q1, Q51, Q54

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1 Introduction

Climate change has posed a threat to past, current, and future maize production as a result of fluctuations in climatic variables (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 the staple food for about 67 to 83 per cent of the nation's population, and is also used as feed for livestock (Alberts et al. 2019). Thus, any change in climate that influences the production of maize would result in serious socio-economic problems such as food insecurity and low economic growth (Mangani et al. 2018). 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; Estes et al. 2013; Mangani et al. 2018; Nxumalo 2014; Walker and Schulze 2008). These studies suggest different results regarding the impact of climate change on maize yield in the country. For instance, Nxumalo (2014) suggests that an increase in temperature of about 2°C will result in a 1.6 per cent increase in maize output in the Jozini Municipality area of South Africa. However, the majority of proponents oppose this finding. For example, Estes et al. (2013) find that maize yield will decline by 3.6 per cent given a rise in temperature of about 2°C. It therefore shows that 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.

Therefore, this study quantifies the average change in maize yield caused by climate change in South Africa, using a meta-analysis that combined results from 34 studies, summarizing a range of outcomes and at the same time assessing the consensus. The study further assesses 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 was used to estimate the impact of climate change on agricultural incomes (Mendelsohn et al. 1994). Two questions are therefore answered in this study: 1) what is the average estimated impact of climate change on maize yield in South Africa? and 2) what is the impact of climate change on the gross value of maize in South Africa?

2 Research methods

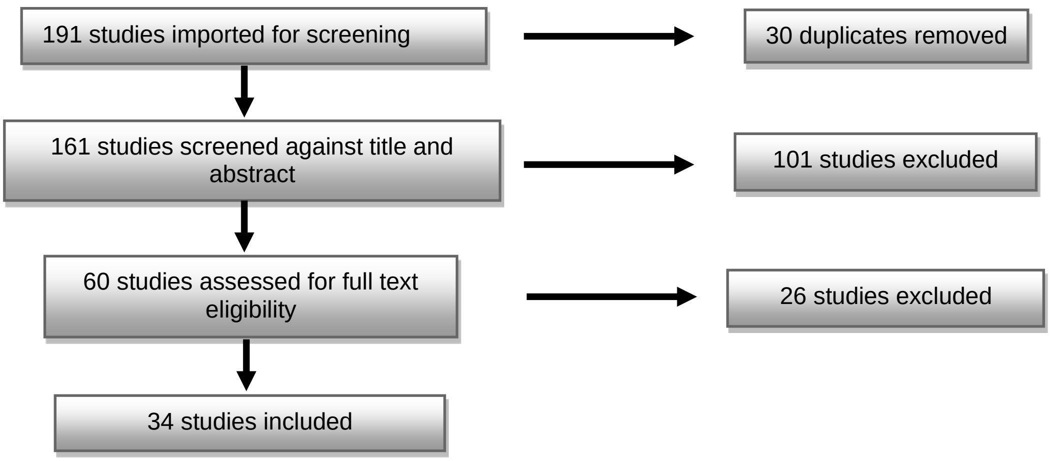
Two methods (meta-analysis and the Ricardian approach) were used in this study. The meta-analysis, as mentioned previously, was used to estimate the impact of climate change on changes in maize yield. The Ricardian approach was used to estimate the marginal impacts of changes in climatic variables on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

2.1 Meta-analysis method

In order to determine the average change in maize yield driven by a change in climate, a meta-analysis of studies that focus on estimating the change in maize yield owing to changes in climatic conditions in South Africa was used. The meta-analysis combined and compared results from 34 studies and reached the estimated average change in yield as a result of global warming. Many of the steps taken in this study follow Challinor et al. (2014), who study crop yields under climate and adaptation on a global scale. An extensive search for studies was done using search terms (climate change assessment, climate variability, rise in temperature, extreme weather events, global; warming, climate impacts, impact assessment, climate change impacts, effect of climate change, maize, crop productivity, farm yields, and crop yields in South Africa). The search was only from the past 30 years and was specific to South African maize yield. All the studies used in this study were extracted from three databases (Scopus, Web of Science, and Google Scholar). These studies are published works of maize yield response to climate change, whether from process based or statistical models, given that they reported the percentage changes in yield under different climate scenarios. The search yielded 161 studies and owing to the inclusion and exclusion criteria that were employed; only 34 studies were selected to run the analysis. The selection process of the studies used in this study is shown in Figure 1. A quality control procedure to remove data points that are not representative of South African maize yields was carried out. Firstly, outliers were examined in order to understand the reasons for differences in the yield results reported by different studies. Any reported change in yield that was above 1.5 per cent was regarded as significant in this study. All the studies that reported yield changes of above 1.5 per cent in either direction were examined in detail. This procedure led to the removal of six data points (Akpalu et al.; Blignaut et al.; Dube and Jury; Matji; Mqadi; Shi and Tao), since they reported yield changes of less than 1.5 per cent. Also, in order to remove any biases in the number of adaptation vs. no-adaptation data points reported in one study, another quality control procedure was done, and it resulted in a further removal of another 16 data points from three studies. After the quality checks, all entries that passed were treated equally in the meta-analysis.

It is also important to consider the geographical spread of data points to avoid potential bias in the meta-analysis. In some instances, the regions where maize production is high are not necessarily the same regions that are being studied in literature. As a result, we considered maize production by province and studies that were carried out in provinces with yearly production that is above 100,000 metric tons. This led to the exclusion of studies that were carried out in the Western Cape province of South Africa. This made the dataset to be a good representative of the major maize producers in the country, thus reducing the bias when estimating the climate change impacts. 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 was calculated using 500 bootstrapped samples. 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 (Cheng and Chen 2019; Hutchison et al. 2018).

Figure 1: Study selection process



Source: author’s illustration.

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.

$$\Delta Y = \beta_1 TMP_i + \beta_2 RFLL_i + \beta_3 ADP_i + \beta_4 MOD_i + \beta_5 SCL_i + \varepsilon_i \quad (1)$$

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.

2.2 The Ricardian approach to the economic impacts 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 economic impacts of climate change on agriculture. The reason for this is that the Ricardian model normally considers farmers' full range of 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 (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:

$$v = \sum_{i=0}^{n} P_i Q_i \,(X, C, S, G, H) - \sum P_x X \quad (2)$$

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 ($P_i Q_i$) 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 higher gross value of maize implies higher net farm incomes, presuming that other factors remain 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:

$$GVM = \alpha_0 + \sum_{j=1}^{m} [\,\alpha_j T_j + \beta_j T_j^2 + \delta_j P_j + \gamma_j P_j^2] + \sum \theta_j \, E_j + \mu \quad (3)$$

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 underestimation. 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:

$$MI_T = \left[\frac{dR}{dT}\right] = \alpha_j + 2\beta_j T \quad (4)$$

$$MI_P = \left[\frac{dR}{dP}\right] = \alpha_j + 2\gamma_j T \quad (5)$$

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

$$\Delta MI_T = MI_{T+1} - MI_T \quad (6)$$

$$\Delta MI_P = MI_{P-1} - MI_P \quad (7)$$

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 and 5 into equations 6 and 7 will yield the following results for the change in marginal impacts after simplifying:

$$\Delta MI_T = 2\beta_j(T_g - T) \quad (8)$$

$$\Delta MI_p = 2\gamma_j(T_f - T) \quad (9)$$

The marginal impacts of changes in climatic variables (+2°C temperature and -15 per cent rainfall) are estimated using the equations 8 and 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 (ZAR). This is also known as total revenue from maize production. The data for this variable was collected as annual data from the Department of Agriculture, Forestry and Fisheries (DAFF) abstract publications (DAFF 2016, 2017, 2018, 2019). 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 the World Bank data archives (World Bank 2018). High 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 economists, Adam Smith and David Ricardo, suggest 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**:** This is the producer price (in South African 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 2019 DAFF abstract (DAFF 2019).

Irrigation $LIRR_t$**:** Given the global rise in temperature generated by climate change, large scale and medium scale as well as some few smallholder farmers tend to adapt by irrigating their farms to continue producing high yields (Mango et al. 2018). 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 is also presented in natural logarithms in the analysis, with 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 is 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 (World Bank 2018).

Data sources and type

This study used time series data for the period 1987–2018 for all the variables used in the Ricardian model for the economic impacts. This time series data were used to investigate the economic impacts of climatic variables on the maize industry. All the data were obtained from secondary sources, namely Index Mundi, World Bank, and DAFF. Table 1 provides a summary of the definition of variables used in the Ricardian model, their unit of measurements, as well as the a priori expectations for all the exogenous variables used.

Table 1: Definition of variables

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

Source: author's elaboration.

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 per cent 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 2 presents the stationarity test results, suggesting that four variables were stationary at level and the other two became stationary after the first difference.

Table 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

Note: ***, ** and * represent 1%, 5%, and 10% levels of significance, respectively.

Source: author's computations.

A multicollinearity test was done using the correlation matrix to ensure that there were no highly correlated variables in the model. With multicollinearity, it is difficult to isolate the individual effects of the explanatory variables from the dependent (Gujarati 2004). The results for multicollinearity are available upon request to the author.

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 per cent level of significance to reject the null hypothesis of no normality (Gujarati 2004). As shown in Table 3, the probability value (0.8084) suggests that there are normally distributed residuals from the estimation, satisfying in this manner 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 per cent level of significance. The results presented in Table 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 per cent. Any value of the probability value less than 5 per cent suggests a model misspecification. However, the results given in Table 3 show that the model is correctly specified, as the probability (p-value = 0.3769) is above 5 per cent. Therefore, this ensures that the results estimated from the model were valid for interpretation.

Table 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

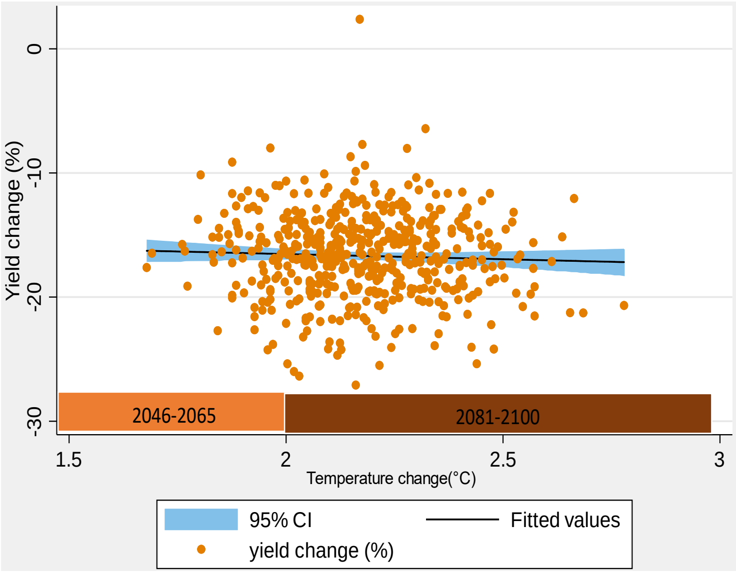
Source: author’s computations.

3 Results

Physical impacts of climate change on maize production

As shown in Figure 2, the majority of studies reported yield changes that are above -10 per cent, 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 per cent. The average change in yield as a result of climate warming is about -16.7 per cent (calculated from 500 bootstrapped samples) at 95 per cent confidence interval (shown by the blue bend), and this effect continues to rise as the temperature increases. Effects are greater for temperatures above 2°C, which are expected in the 2081–2100 year range (highlighted brown region) as compared to the 2045–65 year range (highlighted orange region), where temperatures are expected to rise by no more than 2°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.

Figure 1: Percentage change in yield as a function of temperature



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

Note: shaded blue band indicates the 95% confidence interval.

Source: author's computations.

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, there is a high significance (t = -3.72; p-value = 0.001) of temperature changes, which means temperature change is an important factor to be considered when investigating the impacts of climate change on maize yield. A 1°C change in temperature would result in an average of 8.27 per cent yield loss. Furthermore, the model showed a significant (t = 1.76; p-value = 0.089) positive influence of rainfall with a 0.79 per cent change in rainfall. 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 0: 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

Note: ***, ** and * represent significance at 1%, 5%, and 10% levels.

Source: author's computations.

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 and precipitation loss on the gross value of maize (proxy for farm incomes). As shown in Table 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 per cent increment associated with a 0.23 per cent 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 per cent in the gross value of maize per 1°C. 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 1: 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

Note: ***, ** and * represent significance at 1%, 5%, and 10% levels.

Source: author's computations.

From the estimation presented in Table 5, the impacts of climate change were therefore estimated, using a representative concentration (RCP) 8.5 climate change scenario, which states that temperature will rise by 2°C–3.7°C, and rainfall will decrease by 15 per cent between 2046 and 2100. Looking at the margins estimated at means, the marginal effect of a 15 per cent decrease in rainfall is statistically significant (t = 7.34; p-value = 0.000), showing a 13.11 per cent decrease in the gross value of maize at 95 per cent confidence interval. Similarly, the marginal effect of a 2°C increase in temperature is statistically different from zero (t = -2.75; p-value = 0.012), suggesting a decrease of 89.2 per cent 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 per cent between 2046 and 2100, *ceteris paribus*. The results of the marginal impacts of climate change are shown in Table 6.

Table 2: Marginal impacts of an increase in temperature by 2°C and a fall in rainfall by 15 per cent 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

Note: *** and ** represent significance at 1% and 5%, respectively.

Source: author's computations.

4 Discussion

This is the first study to investigate both the physical and economic effects of climate change on maize production in South Africa through a meta-analysis (for physical impacts) and a Ricardian analysis using time series data (for economic impacts). Many studies (Benhin 2008; Gbetibouo and Hassan 2005; 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 the national level to arrive at the estimated impacts for South Africa.

In terms of physical impacts, the results from the meta-analysis show that yield is going to fall by an average of 16 per cent, 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 challenges in ensuring food security and reducing poverty (Abraha and Savage 2006; Jones and Thornton 2003; Lobell and Burke 2010). Yet again, this decrease in yield due to climate change conflicts with 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 (2018), the South African population is growing at an annual rate of 1.2 per cent. Given the yield decreases projected in this study, some problems associated with hunger such as poor nutrition will also potentially rise.

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 evaluated the economic impact of climate change on major South African field crops. This result has major implications for the quick adoption of heat tolerant maize varieties as compared to their 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 per cent, 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.

5 Conclusion and recommendations

As appraised by several studies (Dale et al. 2017; Du Toit et al. 2002; Challinor et al. 2014; Mangani et al. 2019; Mikemina 2013), climate change has been acknowledged as a serious global concern for food production. This problem translates into serious effects on livelihoods and human life, for example food insecurity and conflicts owing to food shortages. Therefore, climate change remains a concern for policy makers. 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 provide a guide for policy makers regarding what to consider when addressing the effects of climate change 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 strategies, including the wide adoption of heat resistant maize varieties in South Africa. The study also recommends 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. It is also recommended that data enumerators should start reporting farm net revenues at a national level in order to guide future studies to be carried out at a country level.

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