



Article Simulating the Impacts of Climate Change on Maize Yields Using EPIC: A Case Study in the Eastern Cape Province of South Africa[†]

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Abstract: Climate change has been projected to impact negatively on African agricultural systems. However, there is still an insufficient understanding of the possible effects of climate change on crop yields in Africa. In this study, a previously calibrated Environmental Policy Integrated Climate (EPIC) model was used to assess the effects of future climate change on maize (Zea mays L.) yield in the Eastern Cape Province of South Africa. The study aimed to compare maize yields obtained from EPIC simulations using baseline (1980-2010) weather data with maize yields obtained from EPIC using statistically downscaled future climate data sets for two future periods (mid-century (2040-2069) and late century (2070-2099)). We used three general circulation models (GCMs): BCC-CSM1.1, GFDL-ESM2M and MIROC-ES under two Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5, to drive the future maize yield simulations. Simulation results showed that for all three GCMs and for both future periods, a decrease in maize production was projected. Maize yield was projected to decrease by as much as 23.8% for MIROC, RCP 8.5, (2070-2099). The temperature was projected to rise by over 50% in winter under RCP 8.5 for both future periods. For both future scenarios, rainfall was projected to decrease in the summer months while increasing in the winter months. Overall, this study provides preliminary evidence that local farmers and the Eastern Cape government can utilise to develop local climate change adaptation strategies.

Keywords: climate change; agriculture; crop modelling; yield; future climate scenarios

1. Introduction

Climate change is anticipated to significantly impact the resilience of agricultural systems in semi-arid developing countries such as South Africa. The Intergovernmental Panel on Climate Change (IPCC) has projected that increases in greenhouse gases, particularly carbon dioxide (CO_2), are expected to modify global climate by increasing surface air temperature, altering rainfall patterns and increasing the occurrence of extreme weather events [1]. While the increased temperature may boost the yields of some crops in some regions by increasing the rate of biomass accumulation [2], the negative effects of climate change such as increased rainfall variability and droughts are expected to far outweigh the positive benefits of climate change [3]. Several studies have predicted a decline in agricultural productivity in most parts of Southern Africa due to increased rainfall variability and elevated temperatures [4–6].

Maize (*Zea mays* L.) is a staple food in South Africa and vital for food security in the country [7]. However, climate change threatens agricultural productivity in South Africa and hence food security and the livelihoods of many subsistence farmers who rely on maize production for their livelihoods [8,9]. A review by [10] showed that maize was projected to decrease by as much as 8–38% under RCP 4.5 and RCP 8.5 scenarios by the end of the



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). 21st century. Several studies have investigated the impacts of climate change on maize production in South Africa. A study by [11] in Southern Africa using a process-based crop model (APSIM) combined with 17 general circulation models (GCMs) predicted a decrease in future maize yields. However, many of these studies focused on the traditional maize growing areas such as KwaZulu-Natal with limited studies focusing on the Eastern Cape. However, many people rely on maize production for their livelihoods in the Eastern Cape [9]. While the Eastern Cape has been predominantly a livestock producing area due to the semi-arid climate, the government is driving efforts to increase cereal production, especially maize, in an effort to increase the region's food security [9,12,13].

Lately, predicting and evaluating the possible impacts of climate change on crop yields has become important in order to develop effective climate change adaptation strategies in agricultural systems. Early knowledge and understanding of potential climate change effects on crops may help farmers and decision makers to make informed decisions that minimise agricultural production risks and take advantage of opportunities arising from climate change [11]. This knowledge of how the future climate may affect agricultural production is important in semi-arid regions such as South Africa, where water scarcity and increasing frequencies of droughts are already limiting crop production [14] and threatening food security.

One way of predicting and evaluating the effects of future climate conditions on agricultural production is by using crop models. Crop models have gained increasing application in agriculture-related research to enhance crop growth, soil water balance and nutrient management under various climate conditions [15,16]. Crop models have also been used to assess the impacts of climate change on crop production and environmental risks [17,18], and explore potential adaptation strategies [19]. In South Africa, studies have applied crop models in the fields of hydrology and agriculture. For example, Warburton et al. [20] investigated the impacts of climate change on the hydrology of catchments. Abraha and Savage [21] assessed the potential effects of climate change on maize yields in the KwaZulu-Natal area of the country. However, most of these studies in South Africa used global climate data to run the crop models. Global climate data may not always be representative of local climate conditions [22].

When simulating future crop yields, variables such as precipitation and temperature are required as model inputs. General circulation models (GCMs) have been created to use different greenhouse gas scenarios and complex earth–atmosphere interactions to project future climate parameters such as precipitation. GCMs are numerical models that use complex mathematical equations to simulate the earth's atmospheric processes and predict climate [23]. GCMs project climate parameters at a resolution of approximately 250 km² [24,25]. While accurate predictions can be made at this resolution at the global scale, the resolution is coarse at the local scale to support local decision making and planning [26]. To reduce the uncertainty involved with the use of GCMs, data from GCMs is usually downscaled either statistically or dynamically to produce local climate data or regional climate models (RCMs) that reflect local conditions more accurately [27].

In the dynamic downscaling method, a regional climate model (RCM) is nested into the GCM to represent a given boundary forcing. Statistical downscaling methods use empirical relationships established between large-scale and fine-scale variables using historical data, for example, statistical downscaling uses historically sourced data such as the quantitative links between the state of the larger-scale climatic environment and local variations. In contrast, dynamical downscaling employs boundary conditions (e.g., surface pressure and wind) and an atmospheric circulation system (principle of physics) to generate high-resolution data sets [28]. However, the dynamical downscaling method is computationally and technically complex and expensive [29], limiting the number of institutions employing the approach. In this regard, coupling local and regional baseline climate data with statistically downscaled GCM outputs provides an invaluable way of reducing uncertainty associated with climate projections. In this study, freely available climate data, statistically downscaled to reflect local weather more accurately, were used for the climate simulations.

In South Africa, research groups such as the Council for Scientific and Industrial Research (CSIR) and the Climate Systems Analysis Group (CSAG) have developed local downscaled future climate data. However, despite the availability of these locally developed, downscaled climate data, few studies have used these downscaled climate data to assess the impacts of future climate change on crop yields in South Africa [30,31]. Therefore, this study aims to compare current and future maize yields under different future climate scenarios. While the focus of this study was not on climate uncertainty, three climate models were compared to reduce the uncertainty of climate change projections associated with different models that could affect crop response.

2. Materials and Methods

2.1. Background

This study follows up on our previous study using the EPIC model in the study area. The previous study [32] provides a detailed description of the model calibration and validation using limited data from field trials on maize at the Cradock Research Farm. This present study applies the calibrated and validated EPIC model to simulate future maize yields using future climate data sets. In this study, only a summary of the model performance will be given. A detailed description of the calibration and validation steps can be found in [32] and additional data on model performance can be found in Appendix A.

2.2. Study Area

Biophysical data for model calibration were collected from the Cradock Research Farm (Figure 1) in the Eastern Cape province of South Africa (32°13'11.09" S, 25°41'11.86" E, elevation 849 m). The area is predominantly fine-loamy mollic ustifluvent [33], with elevated quantities of Beaufort sediments (alluvial sand and silt and colluvial materials). A description of the major soil characteristics at the Cradock Research Farm is given in Appendix A, Table A1. Rainfall in the area is bimodal, with winter rainfall on the western side of the province and summer rainfall on the eastern side. The region receives an average rainfall amount of 341 mm. The area is drought-prone, and since 2015, most of the Eastern Cape has experienced droughts resulting in water supply shortages [34].



Figure 1. Map of study area indicating the dominant farming towns in the Eastern Cape Province, South Africa. The figure is taken from [32].

The Eastern Cape has been predominantly a livestock production area due to frequent droughts and semi-arid nature of the region. In addition, the soils are inherently infertile and prone to erosion [9]. However, to improve food security in the region, government, through programmes such as the Massive Food Production Programme (MFPP) has been on a drive to increase maize production in the area [12]. Maize is a staple food in the area and key to enhancing the region's food security.

Projections by the South African Department of Environmental Affairs [35] predict significant increases in climate variability for the region. Substantial reductions in both annual and daily precipitation have been forecasted for the area [34,35]. The yearly temperature is also anticipated to rise, accompanied by elevated evapotranspiration rates and the likelihood of droughts. An assessment of mid-century (2040–2060) CMIP5 rainfall predictions by Mahlalela et al. [34] estimate a levelling of the annual rainfall cycle over the Eastern Cape, with summer becoming drier and winter becoming wetter. Generally, the Eastern Cape is projected to have elevated temperatures, a higher frequency of extreme rainfall events and drier conditions, especially in summer [35].

2.3. EPIC Model Description

The EPIC model (version 0810) is an agroecosystem model designed to simulate over 70 crops at the field scale using values characteristic of each crop [36]. Crop yield is estimated based on the biomass accumulated by the plant. Biomass accumulation is affected by model parameters such as planting density (PD), photosynthetic active radiation (PAR), vapor pressure deficit (VPD) and the biomass to energy ratio (WA) [37]. The daily stresses caused by extreme temperature, water and nutrient stress or inappropriate aeration are used to correct the potential daily biomass accumulation to daily actual biomass accumulation. The model also requires weather inputs such as precipitation, minimum and maximum temperature, wind speed and relative humidity. Stresses reduce the biomass accumulation and the harvest index using the value of the most severe stress experienced by the crop [38]. To better reflect the specific site conditions, values of location-specific variables such as potential heat units (PHU) accumulated, HI and optimum temperature (OT) have to be adjusted according to the area or region in which the model is to be used [39].

2.4. Field Work

Field trials on maize were conducted by the Agricultural Research Council (ARC) from 1999 to 2003 at the Cradock Farm to assess the yield potential of hybrid maize cultivars within the Eastern Cape Province of South Africa. Data from these trials were used to calibrate and validate the EPIC model. We selected two fields with similar soil characteristics, one for calibration and one for validation. A randomised block design (RBD) [40], with three replications, was used throughout the field trials. The two fields with similarly performing maize hybrids were managed according to the same agricultural management plan developed by the ARC based on local farmers' management practices. The management plan, including planting and harvesting dates, and irrigation and fertiliser application dates, is shown in Appendix A, Table A2. The management practices were performed around the same time each year. Each year, minor changes to the management plan were carried out based on prevailing weather conditions. In the future climate simulations, management practices including planting dates, fertiliser and irrigation levels used during the maize cultivar evaluation trials were used as the baseline management practices being used in the area.

2.5. Model Inputs

EPIC requires weather inputs such as rainfall, relative humidity, temperature and solar radiation. We obtained weather files for the study area from the AgMERRA [41] climate dataset at 0.5×0.5 arc-degree spatial resolution. Soil parameter values including cation exchange capacity, soil texture, bulk density and electrical conductivity were taken from a previous soil analysis in the Cradock Farm. We selected missing soil parameter

values (i.e., soil albedo, organic carbon concentration) from the Harmonized World Soil Database (HWSD) [42] based on the expert opinion given by the Cradock Farm Manager (Mr G. Jordaan 2017, pers. comm).

2.6. EPIC Model Set-Up

2.6.1. Framework

This study used a modelling framework for the EPIC model developed at the International Institute of Applied Systems Analysis (IIASA) [43]. Raster layers on weather, soil and topography were combined and a modelling scheme applied at 5×5 arc-min resolution. A grid was set up for the whole Eastern Cape and then divided into homogenous grids that had similar site properties such as soil texture, weather and elevation. We then chose the grid containing Cradock farm and used one soil profile based on the soil characteristics at the farm [43]. The simulation grid containing the Cradock Research Farm was then chosen for the simulations.

The Priestly–Taylor method was used to calculate the potential evapotranspiration (PET). The Priestly–Taylor method was selected due to the method yielding PET values close to the region's reported values by [44]. The model was run for 31 years, corresponding to the length of the weather records available, with the first 19 years serving as a warm-up period for equilibrating EPIC's soil erosion functions. Agricultural land management in the model was set up according to the dates in the management plan (Appendix A, Table A2). Irrigation and fertiliser applications were carried out in the model using the manual setting. One soil profile (see Appendix A, Table A1) was used for all the simulations.

2.6.2. Model Calibration

The calibration and validation of the model were performed using grain yield data from two fields at the Cradock Farm that had similar soil types. Other data such as biomass accumulation rates and nutrient leaching were not available for model calibration and validation as the trials were only designed to evaluate cultivar stability and potential yield. Detailed steps of the calibration process are given in [32]. Model calibration used data from one field and model validation used grain yield data collected from the other field. Grain yield data were for the five-year period from 1999 to 2003.

2.6.3. Model Evaluation

We used four indicators, namely root mean square error (*RMSE*), the coefficient of determination (R^2), Nash–Sutcliffe efficiency (*NSE*) and per cent bias (*PBIAS*) to evaluate model efficiency.

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(s_{i}-o_{i})^{2}\right]^{\frac{1}{2}}$$
(1)

$$R^{2} = \frac{\left[\sum(O_{i} - O_{mean})(S_{i} - S_{mean})\right]^{2}}{\sum(O_{i} - O_{mean})^{2}\sum(S_{i} - S_{mean})^{2}}$$
(2)

$$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - O_{mean})}$$
(3)

$$PBIAS = \frac{\sum_{i=1}^{n} 100(O_i - S_i)}{\sum_{i=1}^{n} O_i}$$
(4)

where *n* represents the sample number, O_{mean} the observed mean value and S_{mean} the simulated mean value. O_i and S_i are the observed and predicted values of the *i*th observation (*i* = 1 to *n*), respectively. Regarding the *RMSE*, values close to zero signify a good fit between observed and simulated yields [45]. An *RMSE* of zero indicates that the model predicts the observations with complete accuracy. The coefficient of determination, R^2 , has values ranging from 0 to 1, with higher values denoting less error variance [46]. *NSE* varies from negative infinity to 1, with an *NSE* value of 1 representing perfect model fit

between observed and simulated values. In contrast, negative *NSE* values indicate that the mean observed value is a better predictor than the simulated value [46]. The *PBIAS* measures the tendency of simulated data to be larger or smaller than the observed data. *PBIAS* has an ideal value of 0, while positive values indicate model underestimation, and negative values indicate model overestimation [47]. Lastly, the *t*-test evaluated variations between simulated and observed mean values. We considered $R^2 \ge 0.6$, *PBIAS* $\le \pm 25\%$ and *NSE* ≥ 0.4 as satisfactory model performance criteria following [48].

2.7. Climate Data

We used statistically downscaled climate input data from three general circulation models available from the Coupled Model Intercomparison Project Phase 5 (CMIP5) [49]. The climate data were downloaded from the Climate Systems Analysis Group's (CSAG) Climate Information Portal (CIP) (http://cip.csag.uct.ac.za, accessed 27 July 2019). The climate data come from two primary sources—the Computing Centre for Water Resources located at the University of KwaZulu-Natal and the South African Weather Services. Prior to uploading to the CIP, the data are collated and checked for quality by the CSAG [50]. Due to inherent uncertainties in individual models, three GCMs were used to encompass a range of global mean temperature and precipitation changes and consider a wide range of plausible future scenarios. The selected GCMs have been applied previously in South Africa and found to represent the region accurately in terms of projection signal (see [51] for example). The driving GMCs chosen for this study were the BCC-CSM1.1, GFDL-ESM2M and MIROC-ES models (Table 1).

Abbreviation of the Model Used **Driving Regional General** Source **Circulation Model** in this Study Beijing Climate Centre, China Meteorological BCC-CSM1.1 BCC Administration, China GFDL GFDL-ESM2M Geophysical Fluid Dynamic Laboratory, USA Atmosphere and Ocean Research Institute (University of MIROC-ESM MIROC Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology

Table 1. List of driving GCMs and the model abbreviations used in this study.

For future greenhouse gas emission scenarios, two Regional Concentration Pathways, RCP 4.5 and RCP 8.5, for two future 30-year periods, from 2040–2069 and 2070–2099, were chosen to compare two different possible climate scenarios depending on the level of greenhouse gas emissions. The GCAM modelling team at the Pacific Northwest National Laboratory's Joint Global Change Research Institute (JGCRI) in the United States developed RCP 4.5. It is a stabilisation scenario that stabilises the radiative forcing, overshooting the long-run radiative forcing target level, shortly after 2100 [52,53], whereas RCP 8.5 was created using the MESSAGE model and the IIASA Integrated Assessment Framework by IIASA in Austria. The RCP 8.5 pathway is characterised by increasing greenhouse gas emissions over time and represents a scenario that results in high greenhouse gas levels [54].

We used the weather data for 31 years from 1980 to 2010 for the Cradock Research Farm obtained from the AgMERRA database [41] as input data for the baseline simulation with EPIC. Weather data included daily maximum and minimum temperature and rainfall. In the field trials, the time from physiological maturity to actual harvest date was not recorded. Due to this lack of information on the actual time from physiological maturity to harvest, changes in the length of the growing season under future climate scenarios were not included in the simulations.

2.8. Data Analysis

The model output variables for the simulations analysed included economic yield in tonnes per hectare (t ha⁻¹), seasonal irrigation water applied in millimetres (mm), seasonal evapotranspiration in mm, nitrogen (N) leaching as N lost in percolate in kilogrammes Nitrogen per hectare (kg N ha⁻¹) and water use efficiency (WUE) computed as yield per unit of water use (yield/(rainfall plus irrigation) in kg ha⁻¹ mm⁻¹). The means of the output variables for the current scenario were compared to the means of the output variables for the future periods. Model variables were analysed using analysis of variance (ANOVA) computed with the Statistical Package for Social Scientists (SPSS) v21. Prior to ANOVA, Shapiro–Wilks and Levene's tests examined the normality and equality of variance. Tukey's post hoc tests were used to determine the means that significantly varied when ANOVA indicated significant differences. An independent samples t-test was performed to test for mean differences in the output variables between the two future periods, 2040–2069 and 2070–2099. The ANOVA and t-tests were conducted in SPSS v21.

3. Results

3.1. Model Calibration

Before calibration, the following model performance values were observed: NSE = -3.34, RMSE = 3.65 and PBIAS = 28.55. After calibration the following values were observed: NSE = 0.53, RMSE = 1.17 and PBIAS = 0.31. Table 2 summarises model performance after calibration. For the calibration simulation, the model underestimated yields for all years using default parameters. Adjusting the parameters, Parm 20 (microbial decay rate coefficient), Parm 47 (slow humus transformation rate), Parm 52 (tillage effect on residue decay rate) and WSYF (minimum harvest index) decreased the *RMSE*% from 32.4% to 11.4%, while the *NSE* value increased from negative values to 0.47. Adjusting PHU improved model performance with a PHU value of 2480 producing the smallest *RMSE*% (10.7%) value between observed yields and simulated yields. Further adjustments of PHU from 2480 did not produce any improvement in model performance. After PHU adjustment, model performance came within the range set for satisfactory model calibration (i.e., $R^2 > 0.6$ and $PBIAS < \pm 25\%$). Further calibration of the crop parameters HI and WA was therefore not conducted. The relationship between observed and simulated grain yield is given in Appendix A, Figures A1 and A2.

Table 2. Showing Nash–Sutcliff efficiency (*NSE*), root mean square error (*RMSE*) and per cent bias (*PBIAS*) for calibration and validation [32].

	Observed Mean (t ha ⁻¹)	Simulated Mean (t ha ⁻¹)	NSE	$RMSE$ (t ha $^{-1}$)	PBIAS %
Calibration	11.26	11.23	0.53	1.17	0.31
Validation	11.12	11.23	0.61	1.018	-0.2

3.2. Validation

Observed yields ranged from 9 t ha⁻¹ to 14 t ha⁻¹, while simulated yields ranged from 10 t ha⁻¹ to 12 t ha⁻¹. The following model evaluation statistics were observed: NSE = 0.61, RMSE = 10.18 and PBIAS = -0.2. Model performance was within the set criteria and considered satisfactory. Table 2 summarises model performance for the validation simulation. The model overestimated maize yields for three out of the five years used for validation. In the year 2000, there were unusually high observed maize yields (14.01 t ha⁻¹), which were underestimated by the model. In 2003, the trials had low observed yields, which were slightly overestimated by the model. No indications were given in the management records on why there were unusually high observed yields in the year 2000; however, in the year 2003, management records indicated that the trial suffered a heavy weed infestation. No statistical differences were revealed by the Student's *t*-test (alpha = 0.05) between

the observed and simulated mean grain yields. The relationship between observed and simulated grain yield is shown graphically in Appendix A, Figures A3 and A4.

3.3. Climate Data Analysis

3.3.1. Temperature and Rainfall

All three GCMs revealed average temperature increases from March to October for both scenarios (Figure 2a,b). For RCP 4.5 scenario (Figure 2a), the increase in average temperature was lower than the RCP 8.5 scenario (Figure 2b). The highest monthly average temperature in the RCP 4.5 scenario was $23.7 \,^{\circ}$ C in January and February for the model MIROC and approximately 21 °C for the GFDL and BCC models. The temperature increase was more prominent in the RCP 8.5 scenario and the MIROC model, where average temperatures in June and July were above 10 °C and approximately 6.8 °C higher than the baseline average for the two months. In the months from September to December, the temperatures were similar across all three models.



Figure 2. Monthly average temperatures for the two 30-year future periods compared to 31 years of baseline data, (**a**) RCP 4.5 and (**b**) RCP 8.5.

With respect to temperature differences from the baseline (Figure 3), the GCMs that had the highest temperature increase for the RCP 4.5 scenario were the MIROC model, with a monthly percentage difference from the baseline of about 51% in July and the GFDL model with peaks of more than 40% in June and July for the period 2070–2099. RCP 8.5 showed higher temperature differences from the baseline compared to RCP 4.5 for both climate models and future time periods. The highest percentage difference from the baseline in RCP 8.5 was given by the MIROC model, reaching a peak of 71% in July.

Regarding rainfall (Figure 4), an increase in winter rainfall was observed from May to July for both RCPs with higher average rainfall values in RCP 8.5 (Figure 3b). The MIROC model showed a different trend for rainfall from the other models for both the RCP 4.5 (Figure 3a) and RCP 8.5 scenarios (Figure 3b) with higher average monthly rainfall for the months September to December, showing peaks of about 70 mm in November (Figure 3b). The baseline, BCC and GFDL scenarios also showed peaks in November in the RCP 8.5 scenario but with rainfall peaks lower than the MIROC model (Figure 3b).



Figure 3. Percentage variations from the baseline of average monthly temperatures for the two thirty-year future periods for all three GCMs under the two RCPs, (**a**) BCC RCP 4.5, (**b**) BCC RCP 8.5, (**c**) GFDL RCP 4.5, (**d**) GFDL RCP 8.5, (**e**) MIROC RCP 4.5 and (**f**) MIROC RCP 8.5).



Figure 4. Monthly average rainfall for the two 30-year future periods compared to 31 years of baseline data, (**a**) RCP 4.5 and (**b**) RCP 8.5.

3.3.2. Yield Simulations

Simulation results displayed a similar trend among all the three GCMs used in the RCPs. There was a reduction in maize yield, WUE and seasonal irrigation requirements, and an increase in N leaching and seasonal evapotranspiration for all GCMs under the two future periods (Table 3).

Table 3. Average model output values and mean comparison test for the different scenarios, climate models and future time periods. Different superscript letters on means in the same column indicate significant differences (p < 0.05) revealed by a Tukey's post hoc multiple comparison test. Identical superscript letters on means in the same column indicate no significant differences (p > 0.05).

	Yield (t ha ⁻¹)	Irrigation Water Used (mm)	WUE (kg ha ⁻¹ mm ⁻¹)	N Leaching (kg N ha ⁻¹)	Seasonal Et (mm)
Scenario					
Baseline	$12.24 \ ^{\mathrm{A}} \pm 0.58$	562.89 $^{\rm A} \pm 82.53$	$24.13\ ^{\rm A}\pm 1.33$	$19.91 \ ^{B} \pm 24.17$	907.78 $^{\rm C} \pm 46.79$
RCP 4.5	$11.51 \ ^{\rm B} \pm 1.10$	541.09 $^{\rm A}$ \pm 74.29	$23.46\ ^{\rm A}\pm 1.96$	$36.79\ ^{B}\pm 34.09$	$943.10\ ^{\rm A}\pm 39.08$
RCP 8.5	$10.20\ ^{\rm C}\pm 0.81$	$460.81 \ ^{\rm B} \pm 61.86$	$22.40\ ^{B}\pm 1.19$	$66.13\ ^{\rm A}\pm 53.58$	918.84 $^{\rm B}\pm 40.94$
General Circulation	Model				
BCC-ESM	$10.89~^{\rm A}\pm1.17$	509.23 $^{\rm A}\pm 66.43$	$23.24~^{\rm A}\pm2.34$	49.22 $^{\rm A} \pm$ 41.35	922.45 $^{\rm A} \pm 32.91$
GFDL	$11.05~^{\rm A} \pm 1.32$	510.82 $^{\mathrm{A}}$ \pm 92.8	$22.95 \ ^{B} \pm 1.33$	47.34 $^{\rm A} \pm 52.37$	933.88 $^{\rm A} \pm 45.78$
MIROC	$10.62~^{\rm A}\pm 0.95$	$481.52\ ^{\rm A}\pm 73.55$	$22.58\ ^{BC}\pm 1.09$	56.49 $^{\rm A} \pm 48.18$	936.34 $^{\rm A}$ \pm 44.62
Period					
2040-2069	$11.31 * \pm 0.73$	525.26 *±6 8.77	$23.37 * \pm 0.76$	39.35 * ± 34.14	938.76 * ± 36.59
2070–2099	$10.39 * \pm 1.33$	$475.82 * \pm 81.78$	22.48 * ± 1.33	62.78 * ± 55.77	922.62 * ± 45.13

* Indicates a significant difference at $\alpha = 0.05$ for independent samples t-test. WUE = water use efficiency, Et = evapotranspiration.

Regarding percentage differences between the baseline and future periods, maize yield decreased by up to 23.8% for MIROC, RCP 8.5, (2070–2099). The largest decrease in seasonal irrigation (13.6%) was for GFDL, RCP 8.5 (2040–2069). For WUE, the most significant percentage decrease (22.7%) occurred under MIROC, RCP 8.5, (2070–2099). Concerning N leaching, a significant percentage increase of 375.4% occurred under GFDL, RCP 8.5 (2070–2099). Table 4 shows the percentage differences (future–baseline) between the simulated mean baseline values and simulated mean future values for yield, WUE, seasonal irrigation requirements and N leaching.

Table 4. Percentage differences (future–baseline) between the simulated mean baseline values and simulated mean future values for yield, WUE, seasonal irrigation requirements and N leaching.

Scenario and Period	Yield	Seasonal Irrigation	Water Use Efficiency	N Leaching	
		BCC			
RCP 4.5 2040–2069	-8.2	-5.4	-4.3	-26.4	
RCP 4.5 2070–2099	-7.4	-5.9	-5.1	108.8	
RCP 8.5 2040–2069	-10.7	-5.9	-7.0	148.4	
RCP 8.5 2070–2099	-15.6	-8.0	-14.1	215.5	
		GFDL			
RCP 4.5 2040–2069	0.0	-1.9	0	17.4	
RCP 4.5 2070–2099	-2.5	0.3	-2.8	39.4	
RCP 8.5 2040–2069	-14.8	-13.6	-13.4	207.5	
RCP 8.5 2070–2099	-20.8	-13.6	-21.7	375.4	
MIROC					
RCP 4.5 2040–2069	-8.2	-13.2	-6.6	113.5	
RCP 4.5 2070–2099	-13.1	-8.7	-12.1	178.8	
RCP 8.5 2040–2069	-10.7	-12.9	-9.6	153.2	
RCP 8.5 2070–2099	-23.8	-13.6	-22.7	373.8	

3.3.3. BCC Model

In the second future period, 2070–2099, where the gap from the baseline was more highlighted, maize yield was on average equal to $10.3 \text{ t} \text{ ha}^{-1}$ for RCP 8.5 and $11.3 \text{ t} \text{ ha}^{-1}$ for RCP 4.5. RCP 8.5 2070–2099 gave the most considerable yield difference from the baseline yield (Figure 5a). The seasonal irrigation amount showed a decreasing trend in the future periods compared to the baseline (Figure 5b). The decrease in seasonal irrigation amount was comparable between RCP 4.5 2040–2069, RCP 4.5 2070–2099 and RCP 8.5 2040–2099, with the three periods having similar seasonal irrigation requirements. RCP 8.5 2070–2099 had the largest seasonal irrigation requirement decrease compared to the baseline scenario, with a seasonal irrigation amount 8% lower than the baseline. Future WUE also showed a decrease in WUE was in RCP 8.5 2070–2099, which was 22.7% lower than the baseline WUE. N leaching increased in all future scenarios except in RCP 4.5 2040–2099, where N leaching slightly decrease compared to the baseline scenario (Figure 5d). RCP 8.5 2070–2099 had the largest increase in N leaching compared to the baseline scenario.



Figure 5. EPIC model outputs from the simulations using BCC-ESM climate data. Values are plotted and shown for the two 30-year periods compared to the baseline simulation; (**a**) yield, (**b**) seasonal irrigation, (**c**) water use efficiency (WUE), (**d**) N leaching.

3.3.4. GFDL Model

For the GFDL model, crop yield was similar to the baseline yields but slightly lower (Figure 6a). For RCP 4.5 and RCP 8.5, there were only slight differences in yield in the two future periods for the GFDL scenario. The two future scenarios for RCP 8.5 showed lower yields compared to both RCP 4.5 and the baseline scenario. Seasonal irrigation was similar to the baseline period for the two future periods in RCP 4.5. However, both future periods for RCP 8.5 showed a marked decrease in seasonal irrigation amount compared to the baseline scenario. The largest decrease in seasonal irrigation compared to the baseline scenario was observed for 2040–2069 in RCP 8.5 (Figure 6b). WUE slightly decreased in the future climate scenarios ranging from 15.91 kg ha⁻¹ mm⁻¹ in RCP 8.5 2070–2099 to 20.61 kg ha⁻¹ mm⁻¹ in RCP 4.5 2040–2069 compared to 20.61 kg ha⁻¹ mm⁻¹ in the baseline scenario (Figure 6c). N leaching increased in all future climate periods for all the scenarios compared to the baseline scenario (Figure 6d). RCP 8.5 2070–2099 had the largest increase in N leaching with an average of 91.64 kg N ha⁻¹.

(a)

14

12

10

8

6

4

2

0

Baseline

Yield (t ha-1)





Figure 6. EPIC model outputs from the simulations using GFDL climate data. Values are plotted and shown for the two 30-year periods compared to the baseline simulation; (**a**) yield, (**b**) seasonal irrigation, (**c**) water use efficiency (WUE), (**d**) N leaching.

3.3.5. MIROC Model

The MIROC model showed a similar trend of decreasing yield for all the future periods with respect to the baseline period. Maize yield decreased by up to 23% in RCP 8.5 2070–2099 (Figure 7a). Seasonal irrigation also reduced significantly in the future periods for all RCPs. Seasonal irrigation amount decreased by up to 13% in RCP 4.5 2040–2069 and the two time periods for RCP 8.5 compared to the baseline period (Figure 7b). For WUE, the model simulated a slight decrease over time, particularly in RCP 8.5 2070–2099 (Figure 7c). N leaching increased for all future periods compared to the baseline scenario. RCP 8.5 2070–2099 had the most significant increase in N leaching compared to all the other periods for all three models (Figure 7d).



Figure 7. EPIC model outputs from the simulations using MIROC climate data. Values are plotted and shown for the two 30-year periods compared to the baseline simulation; (a) yield, (b) seasonal irrigation, (c) water use efficiency (WUE), (d) N leaching.

4. Discussion

4.1. EPIC Model Calibration and Validation

Notwithstanding the limited data available to calibrate and validate the model in this study, the calibration results revealed satisfactory agreement between observed and simulated yields. In the initial simulation with default parameters, the agreement between observed and simulated crop yields was unsatisfactory, suggesting the need for calibration. After adjustment of site-specific model parameters, the model performance improved, showing the value of calibrating models with parameters that are site-specific. Our results provide further evidence to support previous studies that have demonstrated that adjusting parameters with local-scale data increase can increase the accuracy of simulations and reduce model uncertainties considerably [55]. For example, Xiong et al. [56] and Angulo et al. [57] demonstrated that fine-tuning PHUs to local conditions could significantly improve model simulation accuracy. In this study, model simulations improved on adjusting the PHU value. The PHUs are closely related to biomass growth and its final yield allotment, indicating the substantial influence of PHU adjustment on simulated crop yields. Trials conducted in the USA by Williams et al. [58] showed that the PHUs required for maize to reach maturity ranged between 1000–2900. In this study, 2480 PHUs brought model performance into the range set for satisfactory model calibration. The ARC in South Africa states that maize typically requires 120 days to mature from the day of planting. However, this period is hugely dependent on weather conditions and 120 days is generally for the warmer traditional maize growing regions in South Africa such as KwaZulu Natal [59]. The Cradock area is relatively cooler than the traditional maize growing regions in South Africa, which may account for the higher PHU value found in this study.

Concerning the HI, the default value in the EPIC model is 0.5, which is representative of HI values for improved high yielding maize varieties [60], similar to the varieties used in the field trials for this study. The default HI value of 0.5 used in this study, has been used in studies such as those by [39,61].

In this study, we did not adjust the biomass to energy ratio (WA) since adjusting PHUs improved the model performance considerably to within the range set for satisfactory model calibration. For example, PHU calibration gave an *RMSE* of 1.17 kg ha⁻¹ and *PBIAS* of 0.31 between observed and simulated yields. The small *RMSE* and *PBIAS* values suggested that no additional WA and HI adjustments were required since the conditions for satisfactory model performance had been met. Regarding WA, we left WA at the default value of 40 kg ha⁻¹ MJ⁻¹ m². Similar studies have also used the value of 40 kg ha⁻¹ MJ⁻¹ m² for WA (see, e.g., [39,62]). The biomass to energy ratio can significantly influence crop yields [63], and [36] explains that WA can substantially alter crop growth and yield rate. Reference [36] further emphasises that WA should be adjusted only as a final resort and based on experimental data.

The EPIC model potentially overestimates yields, even at low observed yields during calibration and validation (see [32]. Studies conducted by [64,65] also found that the EPIC model tended to overestimate low observed yields. It has been suggested that the overestimation of plant available water at field capacity could potentially lead to the overestimation of yields in the dry years by the EPIC model (see [66]). Thus, Kiniry et al. [66] proposed measuring the maximum depth of water extraction using local cultivars as a solution. However, the solution was not applied as it is beyond the scope of the calibration and validation study. The overestimation observed in this study may be attributed to the influence of weed outbreaks. Agricultural management records used during the field trials note that in 2003 the maize fields were affected by heavy weed outbreaks. At the time of model calibration and validation, the EPIC model had not yet been developed to accurately account for competition from weeds [67]. As such, competition from weeds was not accounted for in the simulations, which may explain why the model overestimated the low yields observed in 2003.

4.2. Climate Change Impacts on Maize Yield

Model ensemble results predicted a decrease in maize yield for all future scenarios with a more pronounced reduction in RCP 8.5 2070–2099. This decrease can be attributed to an increased temperature that would shorten the growth stage of the maize crop. Increased temperature increases the rate of accumulation of growing degree days, thereby influencing growth duration. Several studies have shown that temperature increases lead to early crop maturing, allowing less time to accumulate biomass and form grain yield [68–70]. The projected decrease in maize yield in this study agrees with other studies in Southern Africa. For example, studies by [71] projected decreases in maize yield in Zimbabwe under irrigated and rain-fed agriculture. In their study, [71] used the CERES model driven by GCMs (specifically the GFDL and the Canadian Climate Centre Model). Walker and Schulze [72] also studied the response of smallholder maize production in Potshini village, KwaZulu-Natal, South Africa, up to the late 21st century climates. The study by [72] projected a decrease in average maize yields of approximately 30% and showed that more efficient management of fertiliser and manure applications would be a viable management strategy to adapt to climate change.

A study by [73] in Ethiopia for mid-century maize production projected a shortening of maize maturity period by approximately 9–13% due to elevated temperatures. The reduced maturity period would reduce the amount of time the maize crop was able to capture solar radiation and assimilate carbon dioxide, resulting in a reduction in biomass and yield accumulation [74]. Other studies such as those by [75,76] have reported that photosynthesis is affected by elevated temperatures and low water availability, which in turn can reduce the yield. In this study, projections showed an increase in temperature and decrease in rainfall during the early growing season, leading to a reduction in yield. Although rainfall is predicted to be lower in a portion of months in the growing season, studies have shown that maize requires the right amount and distribution of rainfall [77,78]. In this study, GCM projections predicted low rainfall in the critical growing months for maize. While there was an increase in rainfall in winter, the maize plant would already have been affected by water stress, and hence the reduction in yield.

Rainfall can also influence crop yield as water is key to crop growth and development. In this study, rainfall was predicted to decrease in the early months of the maize growing season. Similar to this study [79], found a shift in precipitation during the growing season. The shift in precipitation may affect yield as studies have shown maize to be sensitive to moisture amount and distribution [80]. Furthermore, the decrease in rainfall projected has implications for food production as rainfall supplements irrigation in the study area. Rainfall is the ultimate source of irrigation water in the study area. A reduction in rainfall would lead to decreased flows in the Great Fish River, leading to further water shortages in an already water-scarce area. Further water shortages would significantly impact food production in the area as the Great Fish River supplies most of the irrigation water used by conventional farmers in the area. A previous study by [81] showed that rain-fed maize yields in the Eastern Cape are very low without irrigation even when sufficient fertiliser is provided.

Regarding nitrate leaching, all future simulations predicted significant increases in N leaching. Generally, increases in temperature accelerate phenological development, leading to a shorter growing period and less nutrient uptake. The shorter growing period, coupled with the increased rainfall towards the end of the growing found in this study, can explain the increased leaching for the future period. The increased N leaching found in this study is similar to the findings of [16]. In the study by [16], under future climate scenarios, nitrate leaching was found to increase significantly compared to the baseline scenario. He et al. [16] attributed the increased leaching to the future high temperature stress and increased precipitations, explaining that the high temperature stress and increased precipitations, explaining that the high temperature stress and increased precipitations. This indicates the need to take into consideration the impacts of climate change on N leaching when developing future agricultural land management strategies aimed at maximising the use of N by plants and minimising N losses to the environment.

Considering the predicted impacts of climate change in the study area, farmers may need to obtain financial and technical support to implement on-farm water adaptation strategies such as rainwater harvesting and the use of field water conservation strategies such as mulching. Several studies analysing climate and weather trends in South Africa have shown that average temperatures in the country have increased in the last decades [35,82,83]. A study by [50] on observed and modelled trends for rainfall and temperature for South Africa found significant increases in temperature and rainfall variability in the Eastern Cape. Temperature increases and the decreased rainfall season length predicted in this study suggest that short-term growing maize varieties and drought-tolerant maize varieties may be needed in the Eastern Cape if crop production is to be sustained.

It is worth noting that we did not consider farmers implementing agricultural land management strategies aimed at minimising the effects of climate change in the simulations. This is unlikely to be the case in practice. Agroecosystems are human-managed, and farmers have a variety of possible adaptation options [84,85]. While the study did not show

possible yield changes due to the implementation of climate change adaptation measures, the study does provide a clear picture on maize yield and N leaching rates if no climate change adaptation measures are taken. While there is uncertainty associated with climate projections, several studies in sub-Saharan Africa (e.g., [86,87]) have shown that projections of climate impacts appear robust across model ensembles [11].

However, the results of climate impact studies should not be taken in absolute terms but rather as possible pathways for the future of maize production in the Eastern Cape. Decision makers should consider other factors that may influence crop yield. In this study, the combined influence of other factors such as the development of pests and disease on crop yield was assumed to be fully controlled through appropriate management practices. This study's results can be used by farmers and policymakers to plan how to adapt to the projected increases in temperature and decreased rainfall. It is vital to develop adaptation strategies that consider the projected increases in temperature and minimise N leaching. N leaching represents an economic loss to farmers (N fertiliser not utilised by plants) and a potential water pollutant. It is recommended that studies that test the effectiveness of adaptation strategies and current and future climate scenarios using the EPIC model be carried out in the region.

5. Limitations of the Study

Downscaled climate projections inescapably inherit uncertainties from GCMs. Sources of uncertainty arise from internal variability of the model, the greenhouse gas emission scenario used (RCPs), the statistical downscaling process and imperfections in the GCMs from which the downscaled data were derived. Other sources include using only one crop model (EPIC) to project the impacts of climate change on crop yield. Asseng et al. [88] suggested that ensembles of many crop models could give a better estimate of yield than using one model. However, the use of multiple models was beyond the scope of this study.

The results of climate change effects are prone to many uncertainties resulting from the limited knowledge of underlying geophysical processes of global change (GCM uncertainties) and uncertain future scenarios (emission scenario uncertainties) [19]. Uncertainties in climate projections with respect to climate models can have significant impacts on crop model outputs [89,90]. To reduce uncertainties associated with individual climate models, three different models under two contrasting climate scenarios were selected to capture the full range of changes in temperature and precipitation projected by the models. Reference [91] states that emission scenario uncertainties are less relevant until the middle of the 21st century; hence, the 2040–2069 scenario was chosen as the starting period for future climate simulations.

In this study, carbon dioxide (CO₂) fertilisation effects were not considered due to the lack of site-specific annual data on future CO₂ levels for the periods used in the scenarios. Klein [89] explains that model equations are all subject to variability and uncertainty. As a result, processes included in simulation models, such as CO₂ fertilisation effects, may not always be fully understood or well implemented. For example, Free Air Carbon Enrichment (FACE) experiments indicate productivity increases due to increased CO₂ levels but do not address important co-limitations arising from water and nutrient availability [89]. The magnitude of crops' responses to increased CO₂ levels is thus uncertain and the subject of current debates among researchers [2,92–94]. Biernath et al. [95] argue that many crop models are currently unable to capture the complex underlying processes associated with CO₂ fertilization and are therefore unable to reproduce experimental results.

Additionally, we assumed crop management such as fertilisation to be similar across the future periods, which may not be the case in reality as farmers adapt to changing farming conditions. Additionally, by considering one maize cultivar, we assumed the single cultivar would give similar responses to the impacts of climate change as those of different cultivars.

6. Conclusions

EPIC simulations predict that climate change will negatively affect maize production and environmental water quality in the Eastern Cape. Maize yields are projected to decrease, accompanied by an increase in N leaching. Mitigating the future impacts of climate change will be vital to enhancing food security in the region. Models such as EPIC can help predict and anticipate the possible effects of climate change on crop production and help plan appropriate agricultural land management responses that contribute to sustainable food production in South Africa. In this regard, this study's results have demonstrated that the EPIC model can be considered a valuable tool for exploring the future impacts of climate change on crop yields and the environment. Future studies using EPIC should test the effectiveness of various crop rotation and intercropping strategies based on farmers' current crop rotation and intercropping strategies.

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Appendix A

Supplementary information on the calibration and validation of the EPIC model.

Table A1. Representative soil characteristics of the Cradock Research Farm used as inputs into the Environmental Policy Integrated Climate (EPIC) model (obtained from [32]). Clay, sand, silt, soil organic carbon units are in percentages, whereas bulk density, soil organic carbon and ion exchange capacity are in g cm⁻³ m and (cmol (+) kg⁻¹), respectively.

Coll Descent form	Soil Layer Number			
Soll Parameters	1	2		
Bulk density	1.48	1.52		
Soil depth	0.3	1.2		
Clay	20.4	15.1		
Sand	52.8	42.5		
Silt	26.8	42.4		
pН	6.5	6.5		
Soil organic carbon	0.91	0.2		
Cation exchange capacity	14.3	13.4		

Date ¹	Operation	Туре	Amount
22 October	Planting	Maize	50,000 plants ha $^{-1}$
22 October	Fertilizer application	Superphosphate	$476 \text{kg} \text{ha}^{-1}$
22 October	Fertilizer application	Ammonium sulfate	$330 \mathrm{kg} \mathrm{ha}^{-1}$
22 October	Fertilizer application	Calcium sulfate	$120 \mathrm{kg} \mathrm{ha}^{-1}$
22 October	Irrigation	Furrow	75 mm
15 November	Fertiliser application	Ammonium sulfate	300 kg ha^{-1}
26 November	Irrigation	Furrow	75 mm
10 December	Fertiliser application	Ammonium sulfate	$300 \mathrm{~kg~ha^{-1}}$
17 December	Irrigation	Furrow	75 mm
28 December	Irrigation	Furrow	75 mm
18 January	Irrigation	Furrow	75 mm
8 February	Irrigation	Furrow	75 mm
19 February	Irrigation	Furrow	75 mm
11 March	Irrigation	Furrow	75 mm
5 June	Harvesting	Manual	11 tonnes hectare $^{-1}$ (average)

Table A2. Showing the agricultural management plan used during the study period (table obtained from [32]).

¹ The dates given in the table are not fixed for each year. They indicate the approximate times of year each management activity was carried out during the trial period.



Figure A1. Showing the crop yields (observed and simulated) since the model was in the range set for acceptable model calibration for the study period after PHU calibration (figure obtained from [32]).



Figure A2. Showing the simulated crop yields on observed maize yields with the calibrated maize crop file (figure obtained from [32]).



Figure A3. Simulated yields in the validation simulation using the calibrated model (figure obtained from [32]).



Figure A4. Simulated crop yields (t ha⁻¹) regression result on observed maize yields (figure obtained from [32]).

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