Sensitivity Analysis of Climate Change Impacts on Maize Yield in some Climate Regions of Nigeria using DSSAT Version 4.8.2

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Abstract: - Conducting regional sensitivity analysis of climate change impacts on maize yield in Nigeria is important for understanding vulnerability and complex interactions between climate variables and agricultural productivity vital for developing effective strategies that ensure food security, economic stability and sustainable developments. In this analysis we carried out planting, weather and cultivar sensitivity analysis using Decision Support System for Agrotechnology Transfer (DSSAT) latest version 4.8.2 in Savanna and Sahel climate regions of Nigeria and also forecast yield up to 2100. We used statistical analysis to help identify and quantify the extent to which climate variables are related to maize yields, to reveal how changes in climate might affect agricultural productivity. The correlation and multiple regression analysis show that maize yield is impacted negatively by the solar radiation (SRD), average air temperature (Ta) and evapotranspiration (ET) but positively by precipitation (PRCP). A unit increase in SRD, ET and Ta leads to a decrease in maize yield by about $100kg/ha$, $2kg/ha$ and $200kg/ha$ respectively, while it is increased by about 4kg/ha by a unit increase in precipitation in the region. The P-value < 0.05 of the resulting intercept shows that it is of importance in the developed model. Change in mean temperature has greatest significant impact on maize yield because it has the highest regression coefficient (0.2) with low standard error (0.06). These regression coefficients are location-based so can be calibrated for other regions. Heteroscedasticity test using Breusch-Pagan method is conducted to determine the trustworthiness of the developed equation.

Key-Words: - Climate change, Vulnerability, Food security, Regression, Heteroscedasticity

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1 Introduction

Climate change is a pressing global issue that is reshaping ecosystems, weather patterns, and agricultural landscapes worldwide, [1]. Nigeria's agricultural sector is vulnerable to the impacts of climate change, with changing rainfall patterns, rising temperatures, and extreme weather events severely affecting crop growth and yield, [2]. Maize (*Zea mays*), being a C4 plant highly sensitive to temperature and water availability, is particularly at risk due to change in climate. In Nigeria, a country highly dependent on agriculture, the effects of climate change on maize production are of particular concern because maize being a staple crop provides sustenance for millions of people and serves as a crucial source of income for farmers across the country, [3]. It is one of the most important crops in Nigeria, both in terms of production and consumption, making it a key focus for continuous research in understanding the impacts of climate change on agriculture in the country.

World food crises resulting from shortages of food due to climate change are expected to get more severe in the future, [4]. The largest part of maize produced in Africa goes to human consumption which makes it critical for food security. In Nigeria, a country located in the tropical region of West Africa with a population exceeding 200 million people, climate change poses a serious threat to food security, and rural livelihoods. Agriculture is a cornerstone of the Nigerian economy, employing a large percentage of the population and contributing significantly to the country's Gross Domestic Product (GDP). The vulnerability of Nigeria's agricultural sector to climate change is exacerbated by factors such as limited access to modern farming technologies, inadequate infrastructure, land degradation, and a high dependence on rain-fed agriculture. Smallholder farmers, who make up the majority of the agricultural workforce in Nigeria, are particularly at risk as they often lack the resources and knowledge to adapt to the changing climate conditions, [5]. Understanding the specific impacts of climate change on maize yield in Nigeria is crucial for developing effective adaptation strategies, policies, and interventions that can help mitigate these challenges and build resilience in the agricultural sector. By studying the trends in climate variables, analyzing the relationships between climate change and maize production, and identifying adaptation measures that can support farmers, researchers and policymakers can work towards ensuring sustainable food production, improving livelihoods, and safeguarding food security in Nigeria, [5].

While studies have explored the effects of climate change on agriculture globally, there is a need for more localized regional research focusing on Nigeria climate regions to understand the specific impacts on maize production in different regions of the country. The specific impacts of climate change on maize evapotranspiration and yield in Nigeria have not been well documented which hinders the development of effective local or regional adaptation strategies for community farmers. Despite the importance of maize production in Nigeria, there is limited research on the impacts of climate change on maize crop growth water requirement (ET) and yield in Nigeria. Understanding these impacts is crucial for developing effective adaptation strategies to ensure local food security in the face of a changing climate.

Sensitivity analysis is a valuable tool for farmers to assess the potential impact of various factors such as climate change on their crop yield and make informed decisions to optimize production. By performing sensitivity analysis on maize yield, we can gain valuable insights into the factors influencing maize growth and optimize planting decisions to improve agricultural productivity and resilience to climate change. In this research, after simulation of maize yield using the Decision Support System for Agrotechnology Transfer (DSSAT) latest version 4.8.2, [7], in Savanna and Sahel climate regions of Nigeria, we then employ the correlation and multiple regression analysis to quantify and identify the relationships between climate variables and maize yield, and which of the climate variables most significantly affect maize yield variability based on historical data of climate variables, allowing for evaluation of future implications till 2100. Combination of these analysis techniques enhance the robustness of the findings, allowing for more comprehensive assessments that can guide effective agricultural policies and adaptation strategies.

2 Materials and Methods

2.1 Location

The chosen stations for this research are Akure and Lokoja representing Nigeria's Savanna climate region while Sokoto is chosen to represent the Sahelian hot semi-arid climate region, based on the available maize yield data for calibration and validation. Akure is the capital city of Ondo state in Nigeria, and covers longitude 5.19°E and latitude 7.25°N approximately, while Lokoja is the capital city of Kogi State in North central Nigeria covering approximately longitude 6.7°E and latitude 7.8°N. The coordinates of Sokoto are approximately 5.25°E longitude and 13.06°N latitude.

The Savanna region exhibits a climate that supports a diverse range of wildlife and plant species, with seasonal changes significantly influencing the ecosystem and agricultural practices. The region is characterized by distinct weather patterns influenced by its tropical climate, with high temperature throughout the year. The region experiences dry and wet seasons, with average daily temperature ranging from 25°C to 35°C (77°F to 95°F) or higher with the hottest months typically being March and April. The peak of rainfall ranges from 1000mm to 1500mm occurring between June and September though rainfall in the region lasts from May to October covering the wet season. The dry season occurs between November and April, characterized by little or no rainfall with harmattan wind which brings dry air from the Sahara. The humidity of the region is significantly low during the dry season particularly in January and February feeling especially dry and dusty.

The Sahel region experiences high temperatures often exceeding 35°C (95°F) in the hottest months between March and May yearly. It has a short rainy season from around June to September. The annual erratic precipitation in the region ranges from 300mm to 700mm, with low humidity and high evaporation especially during the dry season. The Sahel region is vulnerable to desertification, exacerbated by factors such as deforestation, overgrazing and climate change.

2.2 Data

The maize yield data used in this research are secondary data from states Agricultural Development Projects (ADP) sourced from previous research papers while the weather data are from National Aeronautics and Space Administration (NASA) power data and Decision Support System for Agrotechnology Transfer (DSSAT) SIMMETEO weather data. The variety of weather data used include daily minimum and maximum near surface temperatures, precipitation (rainfall), solar radiation, humidity, wind speed, as well as the locations' soil data such as soil moisture, type and characteristics. These data are location-specific as they can be critical in understanding microclimates that affect maize yield at each region. The data are prepared in the recommended American Standard Code for Information Interchange (ASCII) format and used as inputs.

2.3 Analysis

To analyze the climate impacts on cereals production such as maize in Nigeria, planting, weather and cultivar sensitivity analysis were carried out using the latest DSSAT version 4.8.2 in Savanna and Sahel climate regions of Nigeria. While the Crop Environment Resource Synthesis (CERES-maize) module of the DSSAT is selected for the simulation of maize yield using NASA historical weather data (as baseline weather data) and DSSAT SIMMETEO weather data as inputs in the simulation of maize yield, the Food and Agricultural Organization (FAO-56) Penman-Monteith module is selected for the ET simulation, ahead of others such as Priestley-Taylor, because of its universal acceptability. The calibration and validation of the simulated maize yield are done by comparing the output yield of the simulation model with observed data to ensure that the model accurately represents real-world conditions. In the calibration process, the model parameters such as growth parameters, soil properties, weather inputs, and management practices are adjusted until the simulated yield closely matches (better fit) observed yield. For the validation, we compare the model's output with new and independent data to assess its accuracy and reliability which helps to ensure that the model is robust.

Some statistical analysis such as correlation, multiple regression and heteroscedasticity tests are also conducted on the results. The correlation coefficient of the average growth weather parameters is calculated for one of the stations (Sokoto) to determine the strength and direction of the effect of each of the parameters on maize yield. The multiple regression analysis is used to determine how the maize yield changes in response to change in average temperature, precipitation, solar radiation and evapotranspiration (ET). It can identify the most important of the maize yield weather predictors and how much yield changes with a unit change in each climate variable. Therefore, multiple regression analysis is used in this sensitivity analysis to understand the relationship between the weather inputs and the maize yield output, it is not a sensitivity analysis on its own. The analysis looks at the coefficients for each independent variable, which indicates the strength and direction of the relationship between the independent variables (weather parameters) and the dependent variable (maize yield). Variables with higher absolute values of correlation coefficients (R) and significant regression coefficients of determination are projected to have stronger impact on yield. The p-values for each coefficient indicates whether the relationship is statistically significant or not while the R-squared value represents the proportion of variance explained by the independent variables. Heteroscedasticity test, using Breusch-Pagan method, is important in this research in determining whether the results of the developed model equation is accurate enough to be trusted, [8].

3 Results and Discussion

The results of the simulation for each of the three stations are as shown in Fig. 1. The scatter plots in Fig. 1 above show observed and simulated maize yield in tropical savannah and Sahel climate regions while Table 1, Table 2, and Table 3, shows the statistical results of comparison between the simulated and observed maize yield in the regions. The observed and simulated yields were observed to have followed similar patterns in all the regions considered within the given years, showing the accuracy of the DSSAT model in simulating maize yield. The model was validated by comparing independent observed and simulated maize yield data from 1997 to 2001 in Akure, tropical savannah region. The results of the simulation reveal that the model has slightly overestimated maize yield in Akure with strong positive correlation coefficient (R) of about 0.84, low Root Mean Square Error (RSME) and Mean Absolute Error (MAE) of about 0.27 and 0.26 respectively. The validation result in Akure station equally reveals a significant high level of positive correlation coefficient of about 0.88 between the simulated and observed maize yield to show that the DSSAT CERES-maize model used can reliably predict maize yield under the varying climate conditions. In Lokoja and Sokoto, strong positive correlation coefficients R of values 0.52 and 0.77 respectively are observed between the simulated and observed maize yield, with their respective RSME values 0.19 and 0.08, and MAE values 0.14 and 0.07 respectively. These results reveal that the best simulation was that of Sokoto (Sahel region) having the lowest RSME and MAE with strong positive correlation coefficient 0.77 as shown in Table 4.

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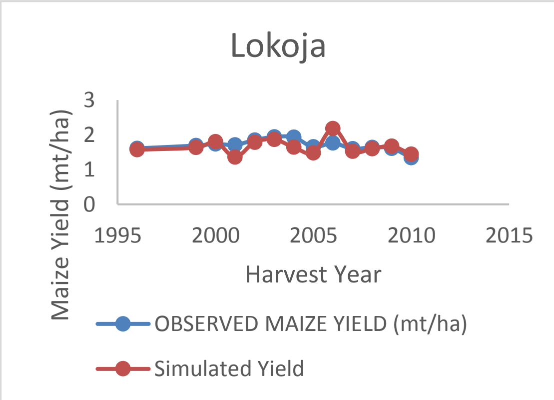

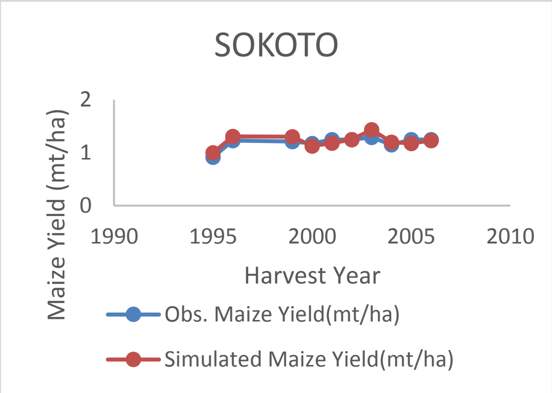

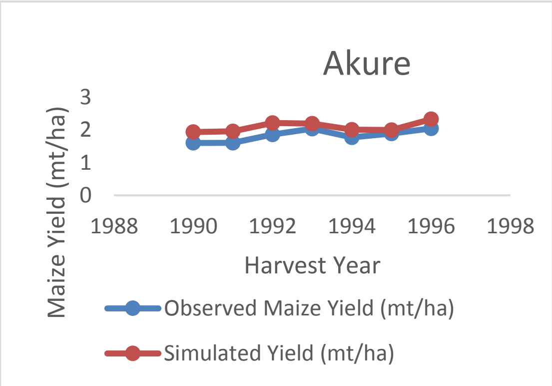

Fig. 1: Observed against Simulated Maize Yield for three stations

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Table 1: Results of the Maize Yield Simulation and Validation for Akure

Akure H-years	Observed Maize Yield (mt/ha)	Simulated Yield (mt/ha)	Difference	
1990	1.601655	1.935	-0.33335	
1991	1.608384	1.962	-0.35362	
1992	1.865426	2.213	-0.34757	
1993	2.042105	2.196	-0.15389	
1994	1.770266	2.012	-0.24173	
1995	1.894782	1.994	-0.09922	
1996	2.045636	2.327	-0.28136	
			RSME	0.274669
			MAE	0.258678
			R	0.84
1997	1.495227	1.881	-0.38577	
1998	1.889943	2.381	-0.49106	
1999	1.937535	2.117	-0.17946	
2000	1.919351	2.293	-0.37365	
2001	2.103266	2.487	-0.38373	
			RSME	0.376572
			MAE	0.362736
			R	0.88

Table 2: Results of the Maize Yield Simulation and Validation for Lokoja

Lokoja Hyear	Simulated Yield	Difference	
1996	1.571	0.039	
1999	1.632	0.058	
2000	1.8	-0.06	
2001	1.361	0.349	
2002	1.786	0.064	
2003	1.866	0.074	
2004	1.643	0.287	
2005	1.483	0.167	
2006	2.178	-0.418	
2007	1.524	0.076	
2008	1.6	0.04	
2009	1.671	-0.061	
2010	1.44	-0.1	
		RSME	0.18521
		MAE	0.137923
		R	0.519936

Table 3: Results of the Maize Yield Simulation and Validation for Sokoto

Sokoto Hyears	Observed Maize Yield (mt/ha)	Simulated Maize Yield (mt/ha)	Difference	
1995	0.917019	1	-0.08298	
1996	1.23	1.31	-0.08	
1999	1.212046	1.3	-0.08795	
2000	1.175041	1.124	0.051041	
2001	1.25	1.178	0.072	
2002	1.25	1.25	0	
2003	1.289568	1.435	-0.14543	
2004	1.148997	1.2	-0.051	
2005	1.245133	1.174	0.071133	
2006	1.24768	1.23	0.01768	
			RSME	0.076115
			MAE	0.065922
			R	0.77

The relatively low Root Mean Square Error, Mean Average Error and strong positive correlation coefficients of the simulation results indicate that there is relatively small difference between the observed and simulated maize yields, hence the DSSAT CERES-maize model used is relatively accurate and likely reliable for predicting maize yield in the regions.

Table 4: Statistics Summary of Observed with Simulated Maize Yields

STATION	R	RSME	MAE
Akure (Savanna)	0.84	0.27467	0.25868
Lokoja (Savanna)	0.5199 4	0.18521	0.13792
Sokoto (Sahel)	0.77	0.06592	0.06592

Planting Sensitivity

The planting sensitivity analysis conducted included sweet corn planting date, population, depth and row spacing. This is crucial for understanding environmental impact that can affect maize growth and yield due to climate change, optimizing planting practices under climate variability, and provides actionable insights for farmers, researchers, policy makers and agricultural planners to adapt and maintain high production levels.

Planting Date

Using DSSAT sensitivity software, the start of planting date, January 1, with a chosen increment of one day stepwise, and iterations for 360-day runs to cover from January to December was considered to evaluate how the weather patterns in each location through the months of the year affect maize growth water requirement (ET) and yield consequently in the Savanna and Sahel regions. The results are shown in Fig. 2. It was observed that the sensitivity analysis for two separate years (2001 and 2010), both produced similar patterns in agreement with the planting dates for optimal yield in the regions. Adjusting the planting date, for at least minimal precipitation throughout the year, the sensitivity analysis result in Fig. 2 revealed that while in Ondo state rainfed maize can be produced throughout the year though with very low yield during dry seasons between January and February, there is near zero production for maize planted in January, early February and from November to December in Lokoja (Tropical Savannah region) and in Sokoto (Semi-arid hot climate zone) within the period, except during the main rainy seasons. Based on the prevailing weather conditions, optimal rainfed maize yield per hectare (above 2.2mt/ha) is obtainable when it is planted anytime between early May to early June in Lokoja, while the best planting period for optimal yield in Akure is between August and September (254 to 283 Julian days) and not later than first week of October in a year, this can give yield as high as above 4 metric tons per hectare as shown in the figures above. The best planting period for optimal maize yield in the Sahelian hot climate region of Nigeria (Sokoto), as observed in the sensitivity analysis, is from late May (Julian day 144) to late June (Julian day 179) when the yield can be as high as 3mt/ha and above. This implies that for resilience agriculture especially in maize production, the time of planting is very crucial for climate change impact mitigation. Adjusting planting time in each of the regions to align with seasonal changes can help maximize maize yields for food security. Proper timing can help farmers to avoid drought periods, flood risks, pests and diseases as adopted in climate-smart agricultural practices.

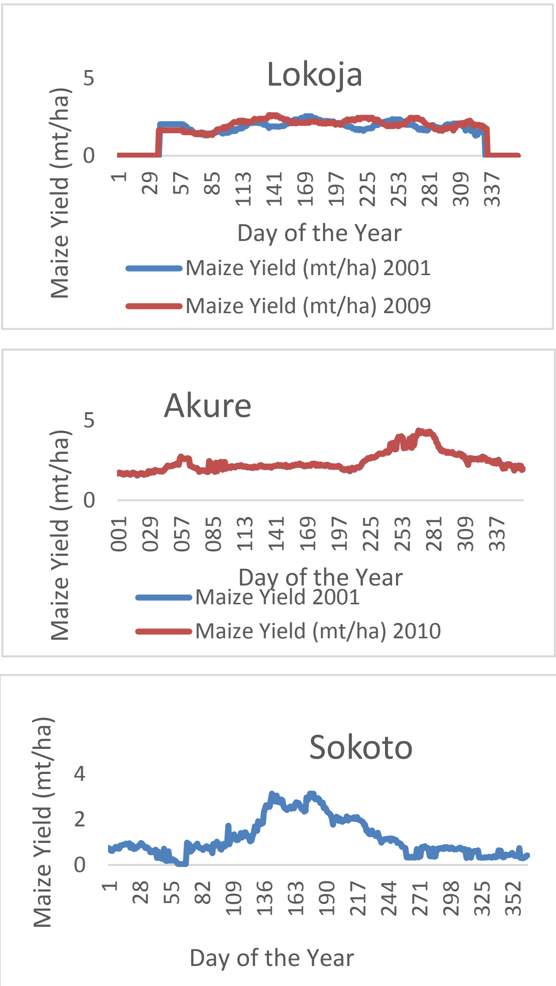
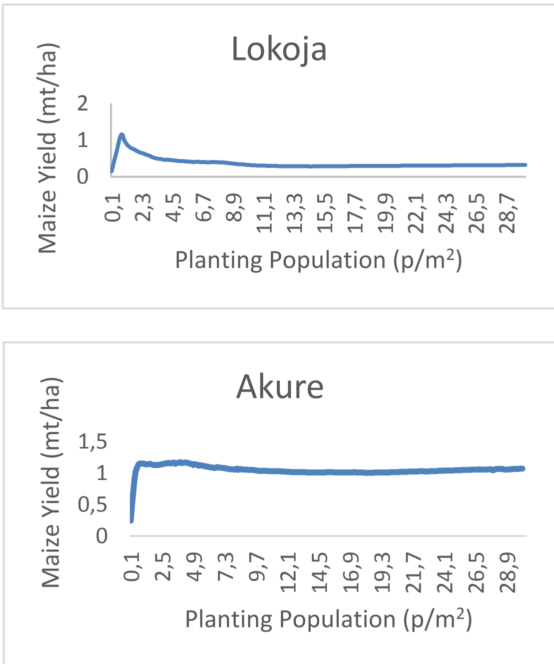


Fig. 2: Planting Date Impact on Rainfed Maize Yield

Planting Population

Based on the weather condition of each region, the maize planting population per square meter is increased gradually by 0.1unit starting from 0.1 to 30.1 and the resulting yield responses are as shown in Fig. 3.

The planting population sensitivity analysis result shows that maize yield increases significantly to a peak of about 0.3mt/ha (300kg/ha) in Sokoto (Semi-Arid Hot climate region), and about 1.1 metric tons per hectare (about 1100kg/ha) in the tropical Savannah region by increasing the planting population gradually from 0.1 up to a maximum of 0.9p/m^2 (approximately 1p/m^2), then significantly decreased as the population per square meter increased beyond 0.9 to about 3.9p/m^2 after which it maintains a nearly steady low yield output even as the population is increased from that 3.9p/m^2 to beyond 30p/m^2. Therefore, for optimal maize yield under the prevailing weather, planting population per square meter of maize should be kept at about 1 plant per square meter. Any population beyond 4 plants per square meter amounts to seed wasting as it would not produce any significant change in yield as a result of Nigeria's weather factors.



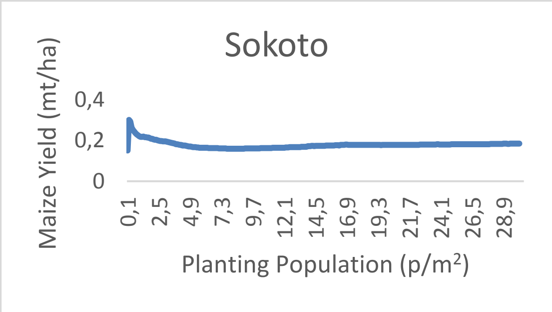
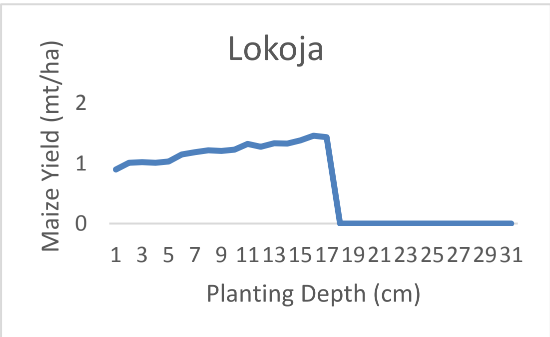


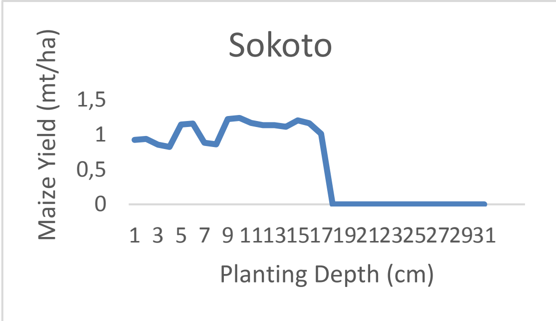
Figure 3: Maize Yield Response to Change in Plant Population Per Square Meter (p/m^2)

Planting Depth

The planting depth for maize is influenced by a myriad of climate elements such as temperature, moisture, soil type and regional agricultural practices which farmers must consider for optimized maize germination and yield. The sensitivity analysis result of the effect of change in maize planting depth on yield in Nigeria's Savanna and Sahel regions is as shown in Fig. 4.

Investigation of effect of increasing maize planting depth from 1.0cm gradually by 1unit to a depth of 30cm, as climate-smart agricultural practices, shows a non-linear significant increase in maize yield output from about 0.898mt/ha or 898kg/ha (at a planting depth of 2cm) to the optimal yield of about 1.459mt/ha or 1459kg/ha (at a planting depth of about 17cm) in the tropical Savanna and Sahel regions. Beyond a planting depth of 18.0cm, there is nearly zero maize yield as shown in the sensitivity analysis result in the figures above. A planting depth from 1.0cm to 1.9cm, and above 18.0cm is not a good choice for optimal maize yield in all the climate regions of Nigeria as observed in the result based on the climate elements of the regions.





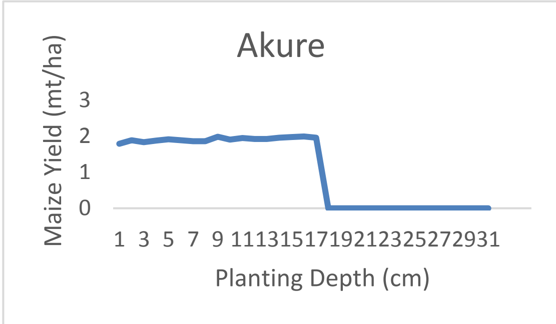


Figure 4 Planting Depth (cm) Variation with Maize Yield (mt/ha)

Row Spacing

Row spacing in maize planting is a significant factor that can influence yield, especially in the context of regional climate change where local climate conditions, water availability, soil fertility and expected pests' pressures have to be critically considered. Starting from a row spacing of 1.0cm up to 300cm iterations, at a unit increase of 1.0cm, the result of the maize yield output variation as shown in Fig. 5.

The result reveals a non-linear significant increase of maize yield as the row spacing increases up to 78.0cm of about 1521kg/ha (1.521mt/ha) optimal yield in Lokoja and Sokoto while it is observed to decrease in Akure as the spacing is increased from 3.0cm. Further increase of row spacing beyond 78.0cm to 300.0cm and above attracts no change in yield in Lokoja while there is nearly zero yield in Akure from about 178cm (about 200cm in Sokoto). The result shows that a maximum row spacing between 75cm and 78cm is best for optimal maize yield in tropical savannah and Semi-Arid hot climate regions of Nigeria. As climate change continues to shift growing conditions, effective adaptive management strategies, including optimized row spacing result from this research, will be essential in ensuring sustainable maize production and food security. It is important for farmers and agricultural researchers to take this collective localized and dynamic approach when determining row spacing to achieve the best results in changing climatic conditions.

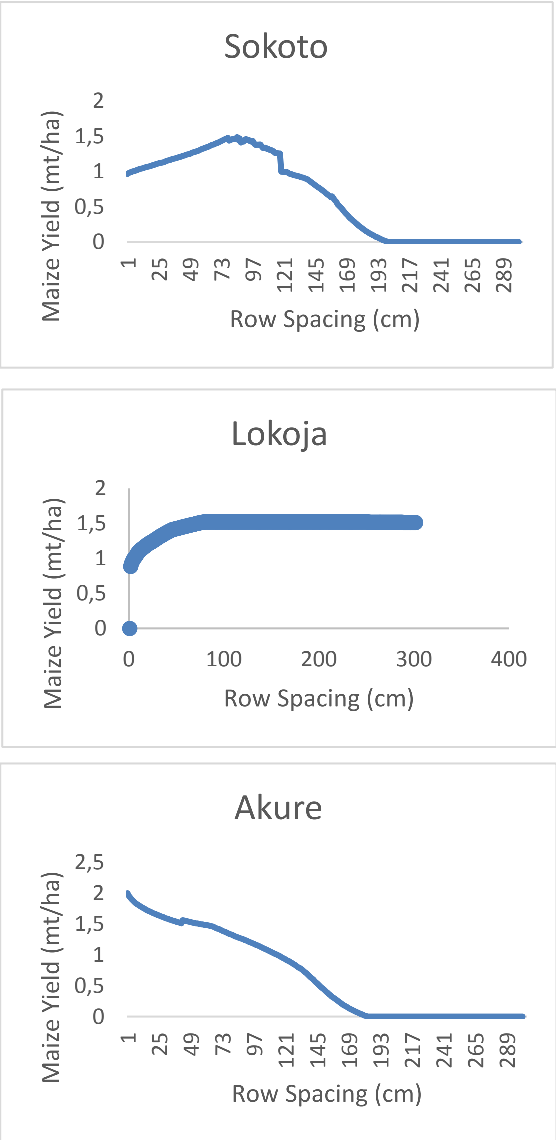


Figure 5 Maize Yield Output Response to Increasing Row Spacing (cm)

Cultivar Sensitivity

Through a systematic approach to sensitivity analysis, farmers and stakeholders can make informed decisions about which maize cultivars to prioritize based on projected regional climate impacts thereby enhancing food security and sustainability in agriculture. The evaluated cultivars include all the 172 maize cultivars listed in the DSSAT version 4.8.2. The findings from the sensitivity analysis are as presented in Fig. 6.

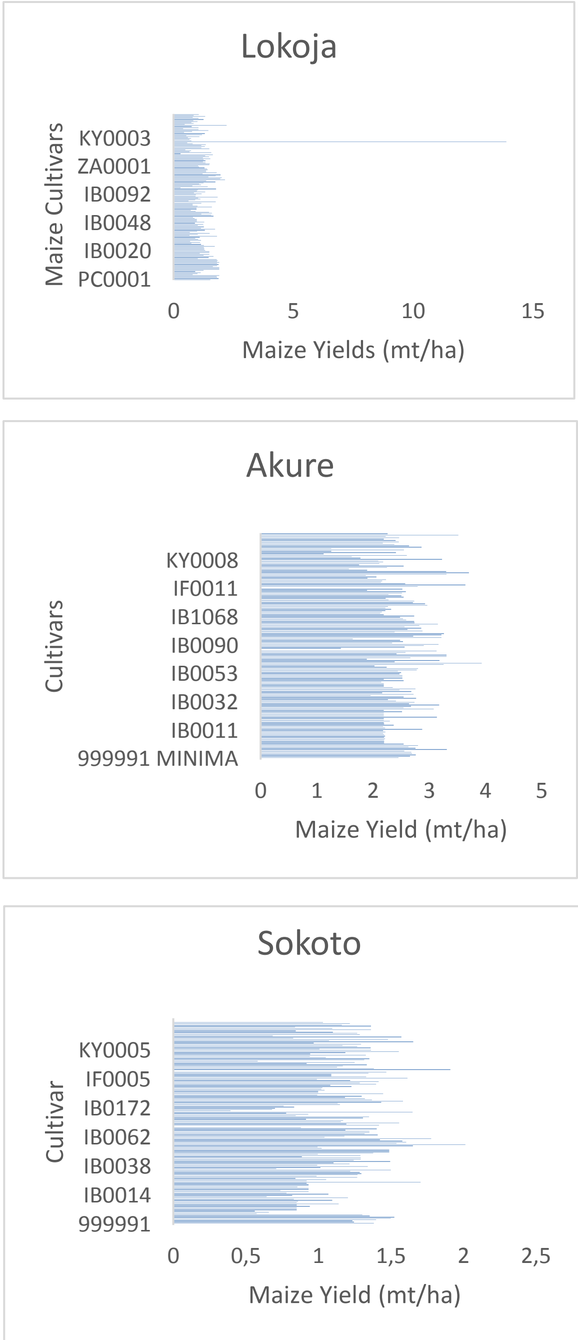


Figure 6 Maize Cultivars Sensitivity Analysis

The sensitivity analysis shows that the cultivar EM0001 H512 stands out among others. It produces about 14mt/ha of maize yield, with its closest rivals KY0016, IB, PC and other KY series having just a little above 2mt/ha under the same conditions. Maize cultivar “EM0001 H512” is a specific variety of maize created through breeding and selection for certain desirable traits such as high yield, disease resistance, and environmental adaptability by the International Maize and Wheat Improvement Center (CIMMYT). In the DSSAT (Decision Support System for

Agrotechnology Transfer) model, the maize cultivar code named "EM0001" refers to the "IITA 899" maize variety. This variety was developed by the International Institute of Tropical Agriculture (IITA). It is common in countries like Brazil, Argentina, Paraguay, Uruguay, and some regions of the United States.

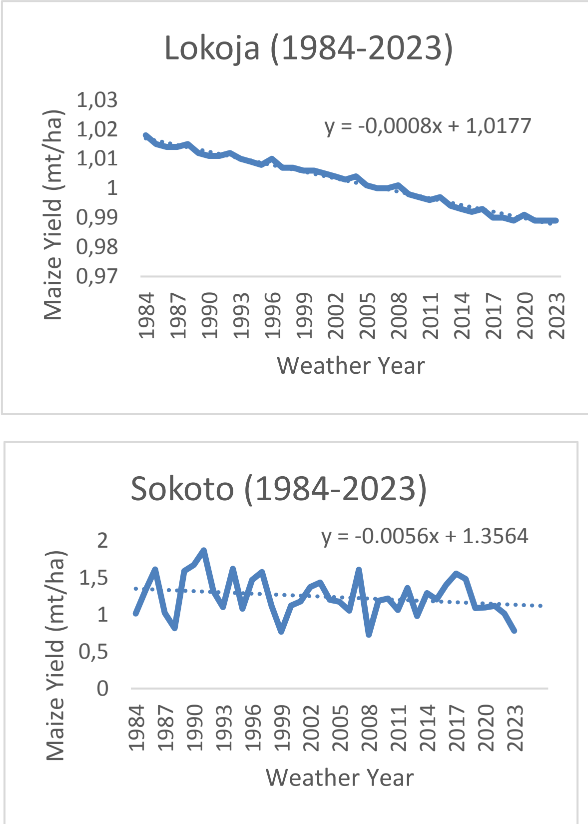
Most of the DSSAT version 4.8.2 available maize cultivars (172 varieties) are cable of yielding well in the regions producing over 2mt/ha, except cultivars type 999991 MINIMA, IB0070 and AC0001 which tend to produce zero maize yield under the same conditions. For optimal maize yield, cultivars that produce above 3mt/ha under the same prevailing climate conditions and considered best for planting in Akure include LONG SEASON 990001, IB0021, IB0027, IB0030, IB0060, IB0061 (the best at about 3.9mt/ha), IB0066, IB0067, IB1053, IB1054, IB0067, IM0001, EM0001, KA0001, KY0009 and EBSL06. In the Semi-arid hot climate region, the IB0056 series produced the highest yields of above 2.0mt/ha, followed by the IV0001 series of about 1.9mt/ha. The KY and IF series are also not performing badly in terms of yield in the Sahel region.

Planting these high yielding cultivars in the regions would improve grain production, reduce food insecurity and poverty among the farmers. Bringing in high yield maize cultivars like EM0001 H512 for distribution to farmers in Nigeria by the government can have numerous benefits for the country, including increased productivity, improved livelihoods, climate resilience, reduced food insecurity, and entire agricultural development.

Weather Sensitivity

Weather sensitivity analysis is crucial for understanding how variations in weather patterns impact maize yield, especially in regions like Nigeria which has diverse climate zones. With ongoing climate change, traditional weather patterns are shifting and sensitivity analysis can reveal vulnerabilities in maize production related to increased temperatures, altered precipitation and more frequent extreme weather events.

The impact of change in climate conditions between 1984 and 2023 is likely to be responsible for the observed maize yield trends in this analysis. The weather sensitivity analysis on maize yield in Fig. 7 shows the fluctuating maize yield per hectare over the years due to



fluctuating weather conditions.

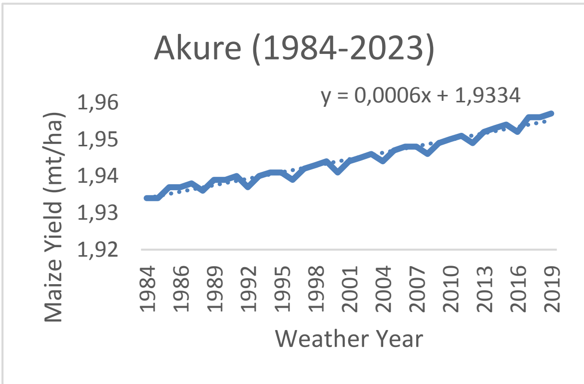
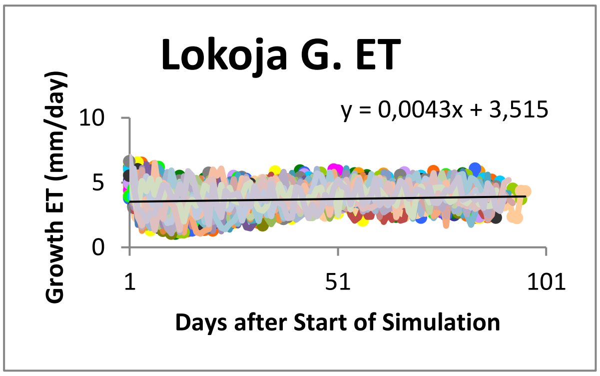


Figure 7 Historical Weather Sensitivity on Maize Yield Trend (1984-2023)



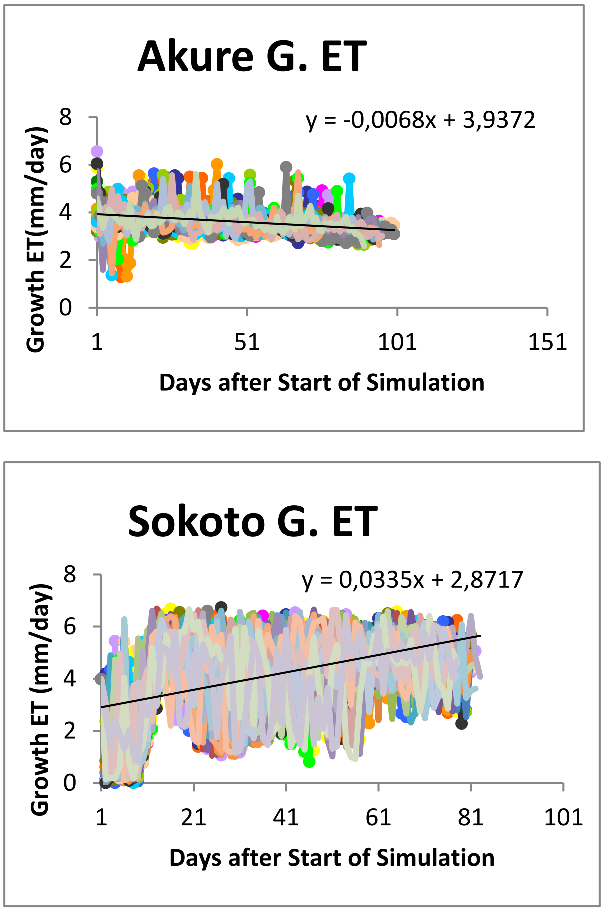


Fig. 8: Growing Season ET (mm/day) Trends (1984-2023)

Within the growing season, the ET weather elements like mean precipitation is observed to be low in Lokoja and Sokoto but high in Akure, while average solar radiation and mean growth air temperature are high in Lokoja and Sokoto but observed to be low in Akure at the maize maturity periods (from about 50 days after planting) over the years. These variations in growth ET within the growing seasons due to climate change, in addition to other environmental factors, might have been responsible for the corresponding observed fluctuating maize yield within the periods in the regions.

The near future prediction up to 2060 analysis in Fig. 9, shows that for every additional year of harvest, there will likely be a decrease in simulated maize yield by about 0.0008mt/ha (0.8kg/ha) same as observed in historical, and 0.004mt/ha (4.0kg/ha) in Lokoja and Sokoto respectively, while it will likely be slightly increasing by about 0.0028mt/ha (2.8kg/ha) per annum in Akure between 2021 and 2060. The yield is observed to be changing at a higher rate per annum in the Sahel (Sokoto) region than any other regions between 2021 and 2060 perhaps due to the more impactful adverse climate change conditions such as higher extreme temperatures, lower rainfall, increasing drought frequency and ET in that region. Conducting further research and analysis on specific factors affecting maize yield in each of these locations may help provide more insights into the reasons behind these trends.

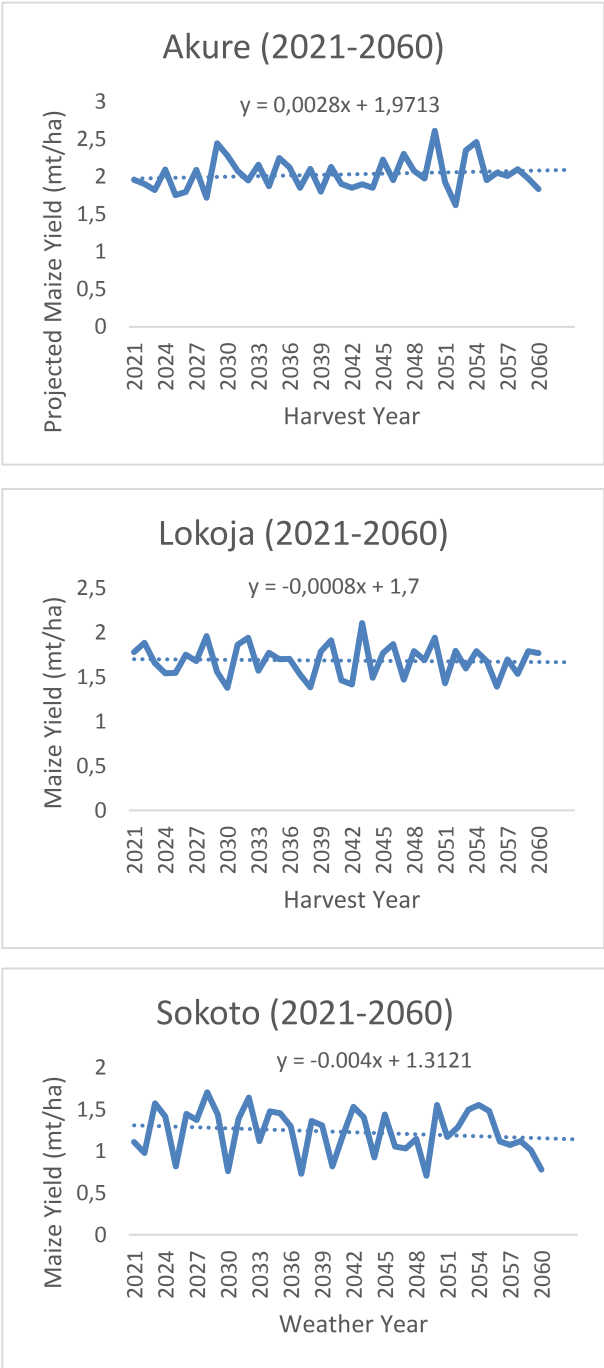


Fig. 9: Near Future (2021-2060) Maize Yield Forecast

For the far future maize yield prediction shown in Fig. 10, it was observed that there is likely going to be slight increase in maize yield for every additional year between 2061 and 2100 in the tropical Savannah and Sahel regions due to the expected slight increase in precipitation as depicted in Fig. 12 and decrease in ET as shown in Fig. 11, as a result of projected slight decrease in solar radiation and average growth air temperature for maize within the growing seasons (Fig. 13). In Lokoja, the average increase in maize yield per annum within the period will likely be about 2.5kg/ha, while it may be about 0.2kg/ha and 0.3kg/ha in Akure and Sokoto respectively.

Despite this projected slight positive trend, it also underscores the need for ongoing research, investment and adaptations in agricultural practices to address the multi-faceted challenges posed by climate change and sustainability. There is need for more efficient sustainable agricultural practices because the projected yield increase is not significant enough to commensurate with the rate of population explosion being experienced within these regions, hence there is need for optimized cereals production such as maize to cater for the growing population. A more substantial yield increase would be desirable to ensure food security and resilience in a changing environment. Continued advancements in climate change adaptations and agricultural technology such as improved varieties, better irrigation systems, and precision agriculture techniques as we go into the future may help increase maize yield over time in the regions.

The cumulative actual and potential ET increase almost linearly through the growing seasons of maize from 2061 to 2100 (figure 11) expectedly. The cumulative ET provides a cumulative (total) measure of water loss over time of the growing season, that is, the sum of ET values calculated at regular intervals during growing days of maize. Figure 12 reveals that the average value of precipitation is expected to increase, from the start of simulation through the growth stage till close to the harvest time.

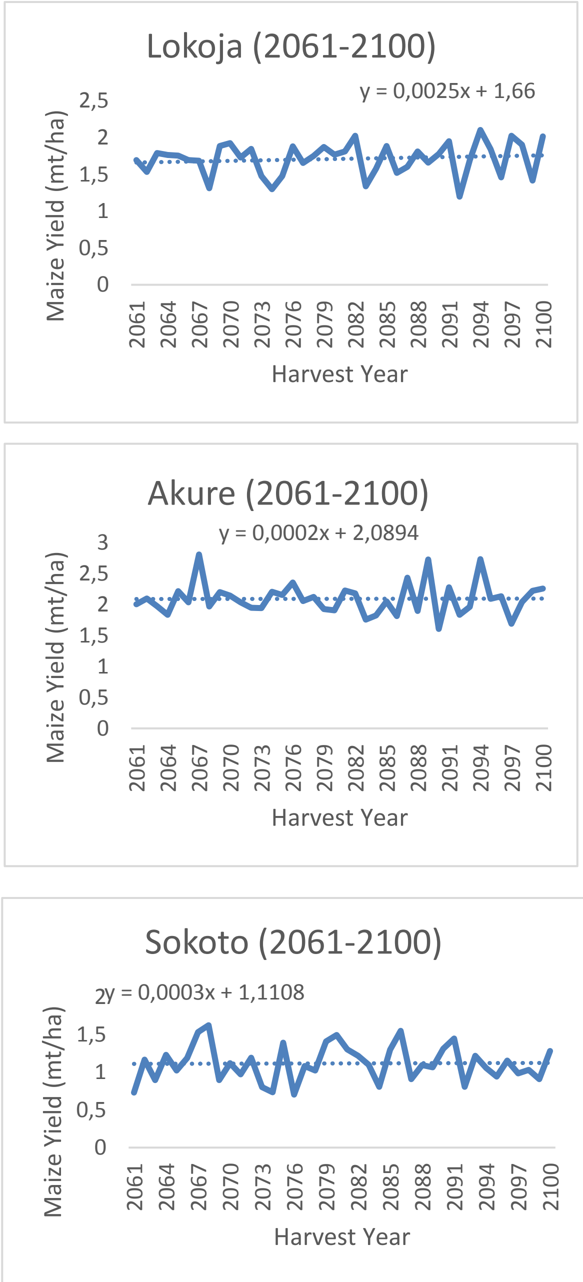
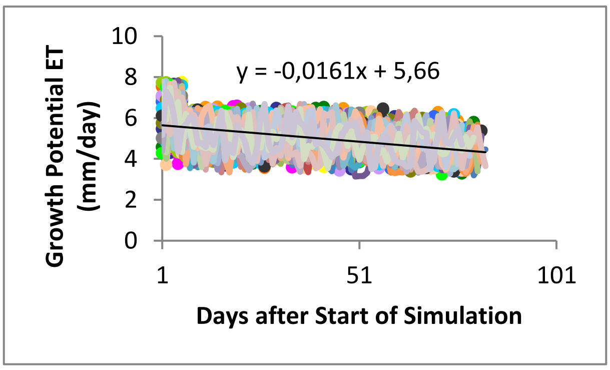


Fig. 10: Future Maize Yield Forecast (2061-2100)



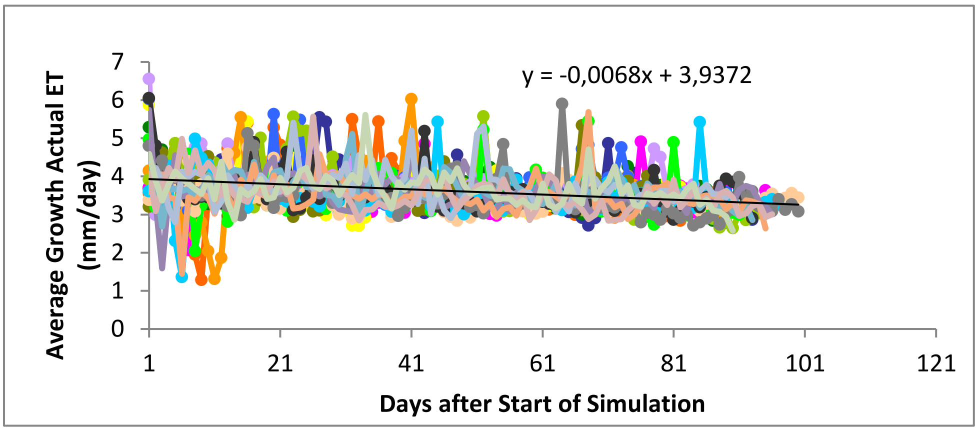
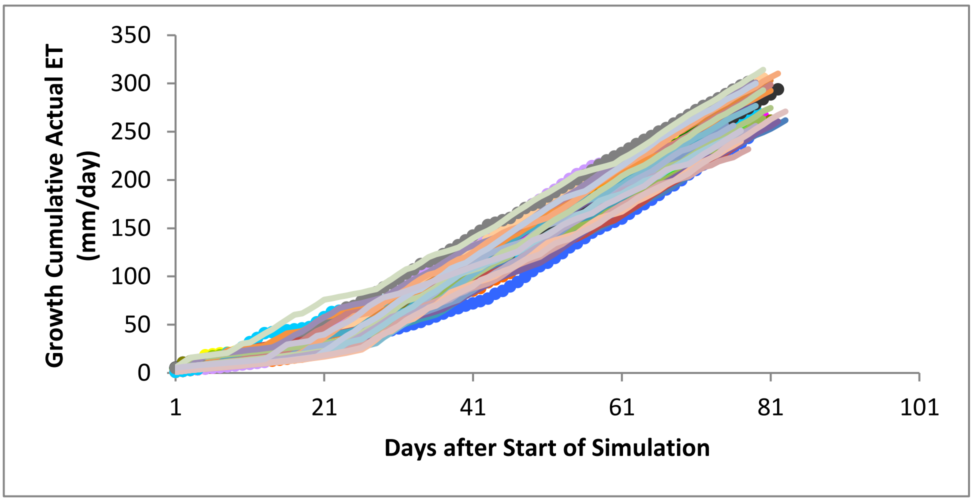
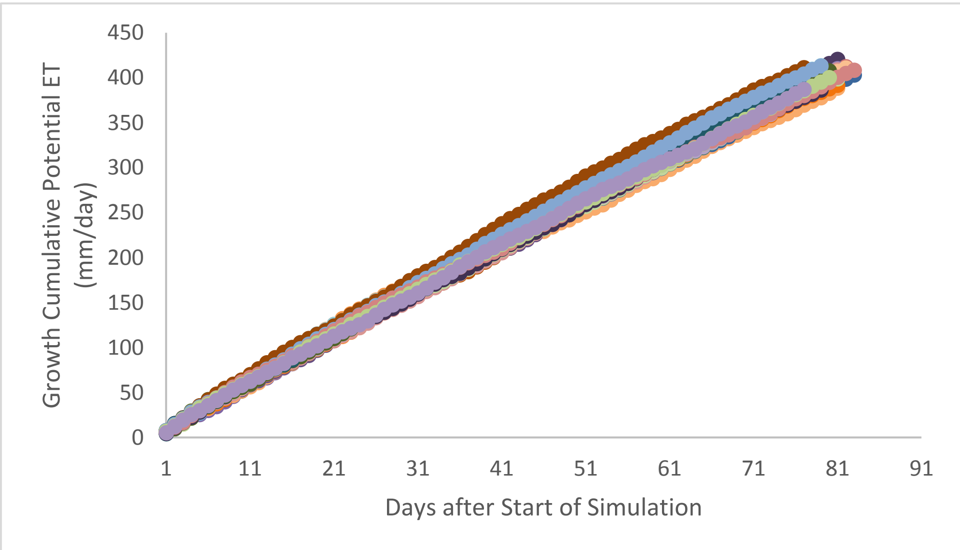


Fig. 11: Growing Season ET (mm/day) Trend





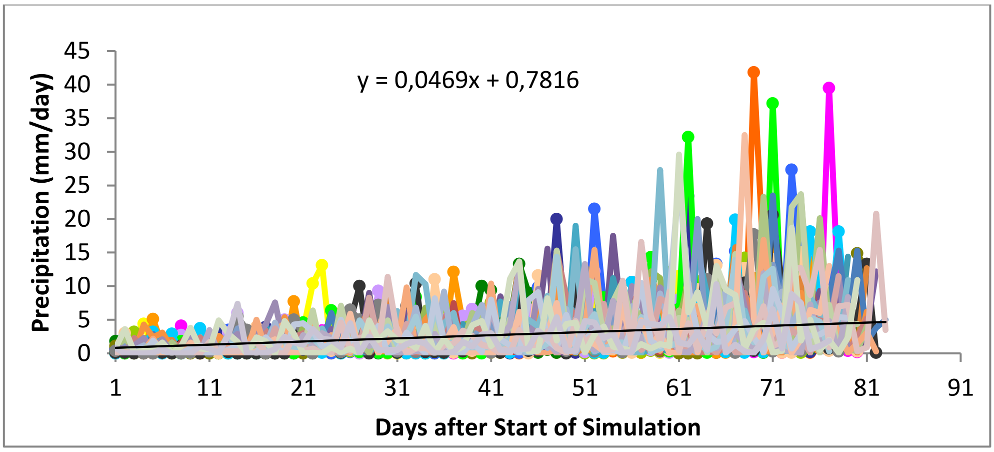
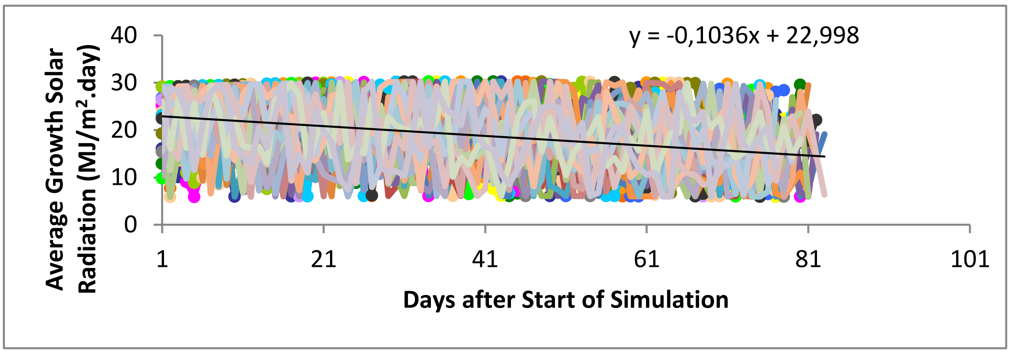


Fig. 12: Growing Season Precipitation (mm/day) Trend (2061-2100)



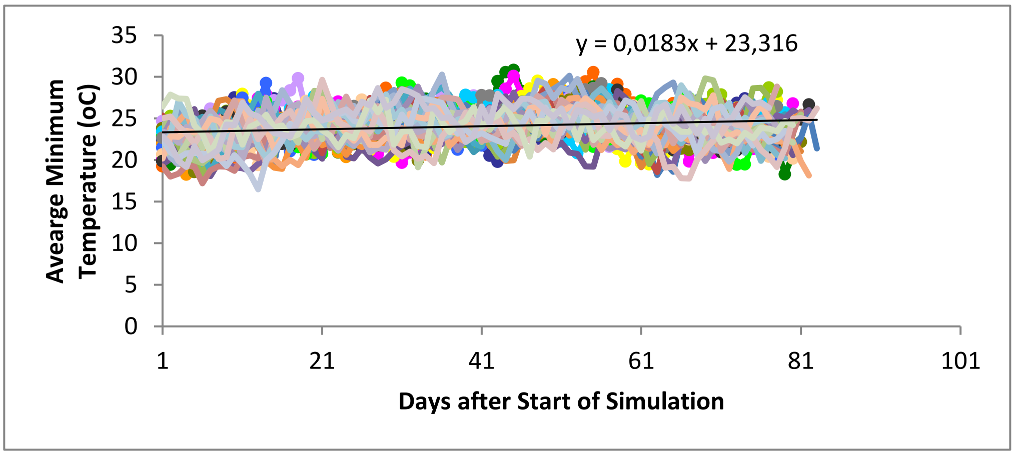
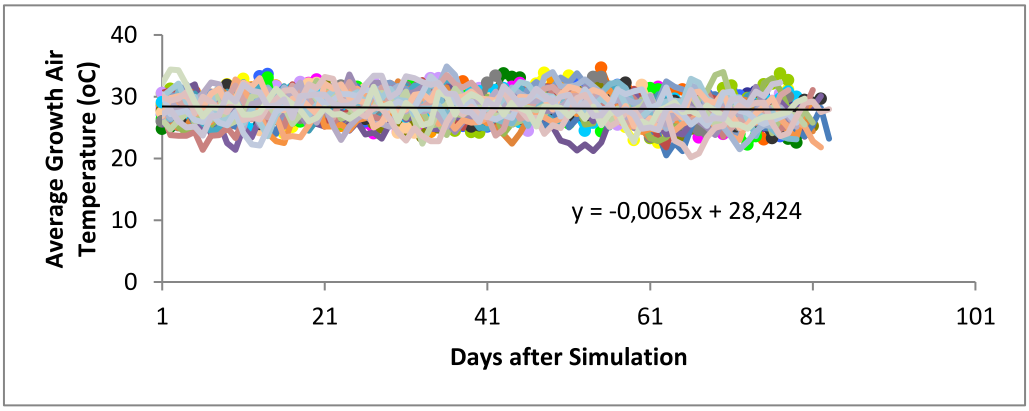


Fig. 13: Growing Season Solar Radiation (MJ/m^2.day) and Average Daily Air Temperature for Growth (^{o}C), TGAD Trends (2061-2100)



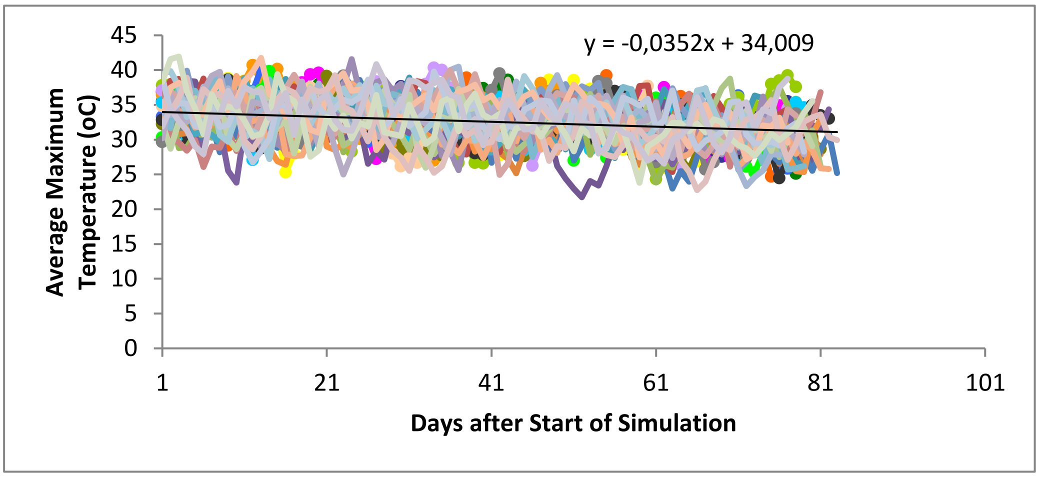


Fig. 14: Growing Season Minimum & Maximum Temperature Trend (2061-2100)

Correlation Analysis
Correlation analysis helps to identify and quantify the extent to which climate variables such as temperature, rainfall and humidity are related to maize yields, understanding these relationships can reveal how changes in climate might affect agricultural productivity. The result of the correlation is shown in Table 5 and Table 6. The highest average maize yield per year (1.7mt/ha) in Sokoto, Sahelian region, is expected to be in the year 2028 corresponding to the year of low average growth ET of about 3.87mm/day, while the least (0.7mt/ha) is expected in 2049 with corresponding high average growth ET of about 4.58mm/day for the near future forecast at relatively stable values of carbon IV oxide and wind speed.

Table 5: Average Daily Growth Weather Parameters from the Sensitivity Analysis

WYEAR	Maize Yield (mt/ha)	Average G. Precipitation (mm/day)	G. Mean Air Temp. (°C)	G. SRAD (MJ/m^2d)	G. Wind (km/d)	G. CO2 (ppm)	G. ET (mm/day)
2021	1.11	6.104938	29.59383	17.64198	86.4	416.0272	4.233444
2022	0.977	5.425641	29.96795	18.56026	86.4	418.0462	4.705333
2023	1.57	4.81625	29.91125	18.0225	86.4	420.425	4.24115
2024	1.413	4.211111	29.62839	19.58272	86.4	420.5	4.057864
2025	0.819	3.963291	30.14937	19.47848	86.4	420.5	3.891785
2026	1.444	2.992405	30.01266	18.61772	86.4	420.5	3.738165
2027	1.372	5.083544	29.32025	17.60633	86.4	420.5	4.00981
2028	1.703	5.022222	29.28395	17.80741	86.4	420.5	3.871123
2029	1.436	6.380247	29.85926	19.78395	86.4	420.5	4.509432
2030	0.761	3.706329	29.88861	17.43165	86.4	420.5	3.662797
2031	1.387	3.970513	29.68718	17.51154	86.4	420.5	4.010654
2032	1.64	5.215	29.81375	17.8125	86.4	420.5	4.128275
2033	1.12	4.896202	29.96582	17.51139	86.4	420.5	4.189177
2034	1.474	4.66747	28.80482	17.23976	86.4	420.5	3.911663
2035	1.453	3.216456	29.76076	17.10127	86.4	420.5	3.84157
2036	1.296	4.539506	29.30247	18.32963	86.4	420.5	3.887926
2037	0.731	5.203846	30.02821	18.00513	86.4	420.5	4.432654
2038	1.359	5.101266	30.10253	18.13671	86.4	420.5	4.332316
2039	1.306	3.859494	29.6557	18.84177	86.4	420.5	3.531051
2040	0.817	4.349367	29.96329	19.42405	86.4	420.5	3.775975

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Samuel O Agele, Vincent O Ajayi, Anselm O Oyem

2041	1.187	3.0925	29.22125	17.72125	86.4	420.5	3.8426
2042	1.528	4.371429	29.99481	18.22597	86.4	420.5	4.312286
2043	1.405	5.305128	30.23462	19.18077	86.4	420.5	4.688321
2044	0.926	3.87284	29.35062	17.88025	86.4	420.5	4.281383
2045	1.436	5.51519	29.53544	17.9443	86.4	420.5	4.395595
2046	1.054	4.242105	30.56053	17.51184	86.4	420.5	4.312118
2047	1.032	3.475309	29.55062	18.51481	86.4	420.5	4.031432
2048	1.146	3.679487	30.5641	17.87308	86.4	420.5	4.239167
2049	0.705	4.910256	30.58077	18.92821	86.4	420.5	4.580885
2050	1.552	4.584615	30.29103	18.02051	86.4	420.5	4.388872
2051	1.168	4.82625	29.6125	17.3525	86.4	420.5	4.38575
2052	1.285	4.238667	31.33733	17.636	86.4	420.5	3.792493
2053	1.493	4.90375	29.88625	18.33125	86.4	420.5	4.316637
2054	1.553	5.079518	28.89157	17.74096	86.4	420.5	4.100325
2055	1.478	4.880488	28.52317	18.40366	86.4	420.5	4.08511
2056	1.117	4.125974	30.78961	20.25714	86.4	420.5	4.359455
2057	1.074	4.579487	30.31154	17.67821	86.4	420.5	4.297051
2058	1.118	5.158442	30.37922	15.50909	86.4	420.5	4.406844
2059	1.014	3.089744	30.36026	18.84615	86.4	420.5	3.794551
2060	0.781	3.410256	29.81538	18.24231	86.4	420.5	3.743256

Table 6: Correlation Coefficients of the Weather Parameters with Maize Yield

G. Prec.	G. Ta	G. SRD	G. U
0.238745	-0.33146	-0.11204	-4.99838E-16

While the average daily air temperature for growth (G. Ta), solar radiation (G. SRD) and wind speed (G.U) revealed weak negative linear correlation coefficients; showing maize yield decreases as their values increase, the average growth precipitation (Prec.) has shown weak but positive linear correlation; showing increase in yield as the value increases within the period. The variable with the strongest impact on maize yield from the correlation coefficient is the average air temperature for growth Ta ($R = -0.33$); a unit increase in growth temperature strongly reduces the average maize yield by about 0.33mt/ha (330kg/ha) as regions such as Sokoto in Nigeria continues to experience global warming going into the future. Following the temperature in terms of strength is the precipitation ($R = 0.24$) but in the opposite direction; a unit increase in growth precipitation in the region tends to increase maize yield by about 0.24mt/ha (240kg/ha) while a unit increase in the growth solar radiation may reduce yield by about 0.11mt/ha (110kg/ha). It should be noted that the weakest of all is wind speed, it has negligible influence on maize yield in the region within the period under consideration.

3.1 Multiple Regression Analysis

Table 7 shows the result of the multiple regression conducted on 40 years data (1984-2023), at 95% confidence level (0.05 significance level). The independent variables with p-values higher than 0.05 are considered statistically insignificant while those that have p values below or equal to 0.05 are considered to be statistically significant.

The correlation coefficient, R value 0.87, indicates very strong positive linear relationship between the maize yield and the weather elements considered, while the R-squared (regression coefficient of determination) value of 0.76 shows that 76% of the variability in maize yield can be explained by the mean daily temperature, solar radiation (SRD), growing season precipitation (PRCP) and evapotranspiration. Solar radiation, precipitation and mean temperature are statistically significant (having p-values $<$ 0.05), while evapotranspiration for the growing season (ETCP) with P-value greater than 0.05 is statistically insignificant hence can be excluded from the resulting equation since the critical elements of the ET (radiation, precipitation and temperature) have been taken care of in the resulting model. The maize yield is impacted negatively by the solar radiation, average temperature and evapotranspiration but positively by precipitation. That is, a unit increase in SRD, ETCP and Ta leads to a decrease in maize yield by about 0.1, 0.002, and 0.2 metric tons per hectare respectively (100kg/ha, 2kg/ha and 200kg/ha respectively) considering each at a time with others kept constant, while it is increased by about 0.004mt/ha (4kg/ha) by a unit increase in precipitation in the region. The P-value < 0.05 of the resulting intercept also shows that it is of importance in the new model to be developed from the equation. Change in mean temperature has the greatest significant impact on maize yield because it has the highest regression coefficient (0.2) with low standard error (0.06).

$$Y = 0.00395(PRCP) - 0.1(SRD) - 0.2(Ta) + 8.76 + \mathcal{E}$$

Where Y is maize yield (mt/ha), PRCP is the average daily precipitation within the growing season (mm/day), SRD is average daily growth Solar radiation (MJ/m^2.day), Ta is mean growth daily temperature (^{o}C) and $\mathcal{E}$ is correction error.

The error $\mathcal{E}$ is determined from the mean of the residual and added to the model equation to correct its coefficients. The residual is calculated as:

$$Residual = Y_{observed} - Y_{predicted}$$

That is, observed yield minus predicted yield. The residuals are summed and the mean calculated for the correction.

Table 8: Residual Output

Observation	*Predicted YIELD (mt/ha)*	*Residuals*	*Standard Residuals*
1	1.556499816	-0.228499816	-1.122122423
2	1.18392885	0.31007115	1.522704906
3	1.213502549	-0.166502549	-0.817664744
4	0.524747277	-0.093747277	-0.460376394
5	0.893392651	-0.006392651	-0.031393184
6	1.153789454	-0.040789454	-0.200309836
7	1.086046325	0.001953675	0.009594154
8	1.042624894	0.005375106	0.026396203
9	1.245180367	0.138819633	0.681718814
10	1.108904443	-0.217904443	-1.070090412
11	1.284057064	-0.014057064	-0.069031768
12	1.524861178	-0.118861178	-0.583706349
13	1.28625695	-0.34625695	-1.70040701
14	2.031245792	0.207754208	1.020244391
15	0.940075698	0.274924302	1.350104915
16	0.359896209	0.041103791	0.201853491
17	0.431672092	0.202327908	0.993596787
18	1.226298186	0.390701814	1.918667919
19	1.597564342	-0.103564342	-0.508586274
20	1.384612855	0.083387145	0.409499608
21	1.272582798	-0.096582798	-0.474301141
22	0.759127044	0.265872956	1.305655347
23	0.78618284	-0.19518284	-0.958508615
24	0.840874795	-0.215874795	-1.060123167
25	1.055757554	-0.025757554	-0.126490818
26	1.637104512	0.210895488	1.035670666
27	0.864994281	0.250005719	1.227734132

28	0.879125503	0.032874497	0.161440878
29	0.963561816	0.075438184	0.370463657
30	0.941828311	0.031171689	0.153078687
31	0.96997556	0.06002444	0.294769473
32	0.798601156	-0.222601156	-1.093155145
33	0.829883218	-0.032883218	-0.1614837
34	1.262758883	-0.353758883	-1.737247684
35	1.212968853	-0.145968853	-0.716827373
36	0.638307535	-0.323307535	-1.587706467
37	1.114450634	0.357549366	1.75586208
38	1.087032526	0.263967474	1.296297856
39	1.982934839	0.075065161	0.368631807
40	1.450790352	-0.330790352	-1.624453265
	Mean of Residual	-7.59115E-16	

The value of the mean of the residual ($-7.59115E^{16}$) is so small that it can be neglected from the equation. The model equation becomes:

$$Y = 0.00395(PRCP) - 0.1(SRD) - 0.2(Ta) + 8.76$$

3.2 Heteroscedasticity Test

The steps in the heteroscedasticity test using Breusch-Pagan method involves the calculation of residual as indicated in the equation below, and the squaring of the residual. The squared residual is plotted, in another multiple regression, as response variable against the weather variables. The R square value from this is used in the Chi-Square test statistics calculated on the original data using the formula:

$$\chi 2 = nR^2$$

where, n is the number of observations ($n = 40$), R^2 is the new R-square value from the squared residual plot (0.011814), such that

$$\chi 2 = 40 \times 0.011814$$
$$\chi 2 = 0.47256.$$

In finding the P-value associated with the calculated Chi-Square test statistic the following command is used in Excel, that is,
P-value=CHISQ.DIST.RT (test statistics, degrees of freedom)

$$df = n - 1 = 40 - 1 = 39$$

∴ P-value=CHISQ.DIST.RT (0.47256, 39)= 1.00

Since, 1.00 is a P-value greater than 0.05, this suggests that there is no significant heteroscedacity present so the resulting model equation above can be used to predict maize yield from the three associated weather parameters satisfactorily.

3.3 Adaptation strategies

To mitigate the impacts of climate change on crop production in Nigeria, a range of adaptation strategies can be implemented. These strategies include:

1. *Improved Water Management*: One potential adaptation strategy to mitigate impacts of climate change on crop production in Nigeria is to invest in irrigation systems that are more efficient and sustainable. Improved water management practices can help farmers adapt to the impacts of climate change on crop yield, ensuring food security and sustainability in the face of a changing climate. By using methods such as drip irrigation or precision agriculture, farmers can ensure that crops receive the right amount of water at the right time, reducing water waste and ensuring optimal growth. This can help mitigate the impact of droughts and water scarcity on crop yield, as well as reduce the reliance on rainfall for irrigation. Another important aspect of water management is proper drainage and soil conservation practices; by implementing measures such as contour farming or cover crops, farmers can reduce erosion and improve soil health, which can in turn lead to higher crop yields and better resilience to extreme weather events. In addition, investing in water storage infrastructure such as reservoirs or rainwater harvesting systems can help

farmers capture and store water during times of abundance for use during periods of drought. This can help ensure a more reliable water supply for crops and reduce the risk of crop failure. By investing in these strategies, farmers can better protect their livelihoods and contribute to global efforts to address climate change. Efficient irrigation systems can help farmers cope with water scarcity and erratic rainfall patterns, as well as exploring rainwater harvesting techniques to supplement irrigation during dry spells.

2. *Adoption of Climate-smart Agricultural Practices (CSA)*: Climate-smart agricultural practices refer to techniques and approaches that aim to increase agricultural productivity, build resilience to climate change, and reduce greenhouse gas emissions. Techniques such as conservation agriculture, agroforestry, and crop rotation can help build soil resilience, improve water retention, and enhance crop productivity in the face of climate change. For example, by planting diverse crops or adopting agroforestry practices can help enhance resilience to pests, diseases, and other climate-related stresses. Furthermore, adopting climate-smart agricultural practices can help reduce greenhouse gas emissions from agriculture, which is a significant contributor to climate change. For example, conservation agriculture techniques such as minimum tillage and cover cropping can improve soil health, reduce carbon emissions, and enhance carbon sequestration. By reducing emissions and enhancing carbon sequestration, farmers can contribute to mitigating climate change impacts on crop yield and promote sustainable agricultural practices. By building resilience, reducing emissions, and promoting sustainable practices, farmers can adapt to changing climate conditions and contribute to global efforts to address climate change. Governments, policymakers, and agricultural stakeholders should support and promote the adoption of climate-smart agricultural practices as a key strategy for climate change adaptation in agriculture.
3. *Use of Improved Crop Varieties*: Farmers can plant drought-resistant and heat-tolerant crop varieties that are better adapted to changing climate conditions. Investing in climate-resilient seeds can help ensure more stable yields in the long run.
4. *Diversification of Crops*: Farmers can adapt by planting a variety of crops that are more resilient to changing climate conditions. This will help reduce the risk of crop failure due to extreme weather events.
5. *Capacity Building and Training*: Educating farmers on climate-smart agricultural practices and providing access to information and resources can help them better adapt to the challenges posed by climate change.
6. *Collaboration and Networking*: Building strong partnerships between farmers, researchers, government agencies, and other stakeholders can facilitate the adoption of climate-resilient technologies and practices, and ensure effective response to climate change impacts on crop production.
7. *Changing Planting Date* – By adjusting the timing of planting, farmers can optimize the growing conditions for their crops and minimize the risks of extreme weather events. Climate change is expected to bring about shifts in temperature and precipitation patterns, which can have significant effects on crop development and yield. By changing the planting date, farmers can align the growth stage of their crops with the optimal environment conditions for growth. For instance, in regions experiencing earlier springs and longer growing seasons due to warming temperatures, planting earlier can help crops take advantage of the longer growing period and potentially increase yield. On the other hand, in regions experiencing increased variability in rainfall patterns, planting later can help avoid water stress during crucial stages of crop development.

4 Conclusion

The Sensitivity analysis is performed, using the DSSAT latest version 4.8.2, for optimized planting decisions to increase maize production output and suggesting maize cultivars that show high resilience to climate change in Nigeria. Based on the characteristic climate of the Sahel and Savanna regions of Nigeria, we found from our research results that the best planting date for optimal maize yield in the regions is from late April to early June, plant population not exceeding average of 1 plant per square meter planted at a maximum depth of 17cm with row spacing of 75cm. The best cultivar for high yield is the EM0001 H512 which can be imported and distributed to farmers because of its high yield output and resilience to change in climate, to prevent food insecurity.

The multiple regression analysis shows that solar radiation, average daily temperature and growth precipitation are the statistically significant weather parameters that impact most on maize yield especially in the Sahelian hot climate region, average daily temperature showing the strongest impact. A good irrigation management is strongly suggested for cereal production in Nigeria to prevent food crisis as a result of increasing temperature and consequently droughts due to climate change. A new model equation whose coefficients are location-based is developed for trial for predicting regional maize yields.

Acknowledgement:
It is an optional section where the authors may write a short text on what should be acknowledged regarding their manuscript.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Yahaya M. is the first author and conceptualized the research with field work.

Ogolo E., Agele S., and Ajayi V., carried out the sensitivity analysis of the research and field work.

Anselm O. Oyem, is the corresponding and lead author, carried out the compilation and editing if the research into the format.

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Conflict of Interest

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Table 7: Multiple Regression Result

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.873204996
R Square	0.762486965
Adjusted R Square	0.735342618
Standard Error	0.21495319
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	5.191595015	1.297898754	28.09008	1.7E-10
Residual	35	1.617170585	0.046204874		
Total	39	6.8087656			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	8.758839218	2.138970439	4.094885586	0.000237	4.416498	13.10118	4.416498	13.10118
SRD	-0.100759356	0.028423431	-3.54493992	0.001138	-0.15846	-0.04306	-0.15846	-0.04306
PRCP	0.003953822	0.001117074	3.539444034	0.001155	0.001686	0.006222	0.001686	0.006222
ETCP	-0.002216995	0.001650942	-1.342866639	0.187959	-0.00557	0.001135	-0.00557	0.001135
Ta	-0.200226219	0.062247551	-3.216612005	0.002792	-0.3266	-0.07386	-0.3266	-0.07386

Table 9: *Heteroscedacity Statistics*

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.108693
R Square	0.011814
Adjusted R Square	-0.10112
Standard Error	0.045924
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.000882	0.000221	0.10461	0.98015
Residual	35	0.073815	0.002109		
Total	39	0.074698			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.040401	0.456983	0.088408	0.930056	-0.88732	0.968126	-0.88732	0.968126
SRD	-0.00337	0.006073	-0.55436	0.582855	-0.01569	0.008962	-0.01569	0.008962
PRCP	8.82E-06	0.000239	0.036952	0.970733	-0.00048	0.000493	-0.00048	0.000493
ETCP	5.77E-05	0.000353	0.163502	0.871063	-0.00066	0.000774	-0.00066	0.000774
Ta	0.001691	0.013299	0.127165	0.899538	-0.02531	0.028689	-0.02531	0.028689