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Title:

ASSESSMENT OF CURRENT AND FUTURE IMPACTS OF CLIMATE VARIABILITY ON MAIZE YIELD IN KANO STATE, NIGERIA

A thesis submitted to Pan African University in partial fulfillment of the requirements for the degree of Master of Science in Climate Change

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DEDICATION

This research work is dedicated to my beloved parents and family for their support and assistance financially, morally and spiritually as well as their hard work in terms of prayer on my studies and my life in general, May Almighty reward them abundantly in this universe and hereafter, Ameen**.**

DECLARATION

I, Maryam Shu'aibu Hassan, hereby declare that this thesis titled "**Assessment of Current and Future Impacts of Climate Variability on Maize Yield in Kano State**" represents my personal work and the result of my own research and it has not been presented in any form, anywhere for the award of a degree in any situation. I also declare that all information, materials and results from other works presented here, have been fully cited and referenced in accordance with the academic rules and ethics. Therefore, all shortcomings in this work are entirely my responsibility.

Hassan, Maryam Shu'aibu ____________ 28/3/2024

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ABBREVIATIONS AND ACRONYMS

CRU TS	Climatic Research Unit Time Series
CHIRPS	Climate Hazard Group Infrared Precipitation with Station Data
CMIP6	Coupled Model Intercomparison Project 6
CIMMYT	International Maize and Wheat Improvement Center
DSSAT	Decision Support System for Agrotechnology Transfer
DJF	December, January, February
GCMs	Global Circulation Models
GIS	Geographical Information System
HadGem3	Hadley Center UK, Met Office
IPCC	Intergovernmental Panel on Climate Change
IITA	International Institute of Tropical Agriculture
IDW	Inverse Distance Weighing
JJA	June, July, August
KNARDA	Kano State Agricultural and Rural Development Authority
MERRA	Modern Era Retrospective-Analysis for Research & Applications
MIROC 6	Japan Agency for Marine, Earth Science and Technology
MRI-ESM2	Meteorological Research Institute
MAM	March, April, May
NASA	National Aeronautics and Space Administration
SON	September, October, November
SSPs	Shared Socioeconomic Pathways

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Abstract

IPCC predicts that climate change will have an impact on agriculture in the future and increase the risk of hunger and water scarcity, the world will need to expand agricultural output to feed an estimated nine billion people by 2050. Therefore, more focus has been placed on the effects of climate change that account for uncertainty in climate projections and the adaptation of crops to it. Agricultural system in Kano State depends largely on natural rainfall as the main source of crop production, and thus, exposed to spatial and temporal variability of the climatic parameters of rainfall and temperature. This study used the GIS and Remote Sensing tool to generate current and future temperature and precipitation maps of Kano State, Nigeria using data obtained from NASA power, CRU and CHIRPS for current scenarios and GCM's CMIP6 for the future scenarios. The results showed an increase in temperature and precipitation in the future through the SSP5,8.5, which might impact the maize yield positively or negatively. A non-parametric statistic of Mann-Kendall and Sen.'s slope estimator alongside multiple linear regression was conducted on the observed data to check the trend of temperature and precipitation over the years, at the same time the regression analysis was done to check whether the dependent variable (maize) can be affected by the independent variables (temperature and precipitation). The findings showed that precipitation and temperature have no significance on maize yield in the study area. Furthermore, for future climate projections and impacts on maize yield, crop data was analyzed in DSSAT model to simulate and forecast future maize yield in the study area. The findings of which leads to the recommendation that other variables such as soil moisture, crop varieties, irrigation and climate-smart agricultural practices be considered for effective increase in maize yield in the study area.

Keywords: CMIP6, SSPs, Climate parameters, Maize yield, Multiple Linear Regression, DSSAT

CHAPTER ONE

1.0. INTRODUCTION

1.1. Background of the Study

Every populated area on the planet is already experiencing the effects of climate change, with human activity responsible for many of the known changes in weather and climatic extremes (IPCC, 2021).The IPCC also predicts that climate change will have an impact on agriculture in the future and increase the risk of hunger and water scarcity. Coupled with changes in consumer habits, the effects of climate change, and the increasing scarcity of water and land by 2050, the world will need to expand agricultural output to feed an estimated nine billion people (Akpoti et al., 2022; Knox et al., 2012). More focus has been placed on the effects of climate change that account for uncertainty in climate projections and the adaptation of crops to climate change(Zhang et al., 2017). Researchers needs effective and timely response knowledge on how climate change may affect crop output (Lobell & Burke, 2010). According to the Intergovernmental Panel on Climate Change (IPCC, 2014a), climatic factors like extreme heat, heavy rain, CO_2 emissions, and cyclones are adversely influencing many facets of agriculture, including food production, distribution, and prices(Chandio et al., 2022). Researchers agree that global climate change can have an impact on the production yields of crops and is an issue that must be addressed for attaining food security.

The subtropics will become drier than the moist tropics, and Africa is projected to experience larger mean annual warmth than the global annual average warming in all seasons. This susceptibility has been attributed to the continent's high rates of poverty, poor capability for adaptation, reliance on rain-fed agriculture, and weak institutional and economic capacity (Cairns et al., 2013). Temperature change is one of the most important challenges in climate forecasts. Projections of future temperatures related with anthropogenic global warming are crucial for every area of human activity and natural systems, including human health, ecosystems, and a range of sectors including as agriculture, energy, and insurance (Murata et al., 2014). Similarly, rainfall trend analysis is crucial in assessing the effects of climate change on water resource planning and management. It has been acknowledged that global or continental scale measurements of past climate are inadequate for local or regional size planning. Thus, historical patterns or future estimates must be evaluated on a regional or local scale. Furthermore, increased food grain production is dependent on the efficient utilization of resources. Crop response to irrigation, fertilizer, and other inputs is determined by factors such as soil, climate, genotype, and management. Developing effective crop management methods in the face of weather and resource uncertainty has significant economic and environmental ramifications.

After all, climate variability already poses a threat to Africa's food security. Furthermore, sub-Saharan African countries are projected to be among the most affected by climate change worldwide. In the last few years, Africa's temperatures have increased at a rate a bit faster than the average global temperature increase. This has resulted in a decrease in food security through reduced crop yields across the continent (Asfew & Bedemo, 2022; Bello, 2021; Kourat et al., 2022; Wang et al., 2018; Yeboah et al., 2022).

Maize Zea mays L. is one of the most important food crops in the world after wheat and rice (FAOSTAT, 2016). Maize has a wide adaptation that is more than other cereals do; hence, it is cultivated in diverse environments around the world. According to FAO, the top six corn upper left producers in the world are US, China, Brazil, Argentina, India, and mexico. Similarly, according to FAO, Nigeria is the largest maize producer in Africa with about 10.2 million tons from 4.8 million hectares in 2018, overtaking South Africa. Nigeria Maize yield for 2018/2019 was about 1.6 tonnes per hectare (FAO, 2018)Agbiz, n.d.). During the last three decades, maize output in Nigeria's savannas, especially in the semi-arid Sudan savanna zone, has expanded significantly (IITA, 2017). Maize has evolved from being a domestic crop often grown in backyards in oversubscribed plots by women and children to a true cash crop providing food, animal fodder and industrial materials. The International Institute of Tropical Agriculture and its collaborators have developed several varieties of maize with varying attributes that could be utilized in various Nigerian zones (Adnan et al., 2020). Maize production has improved with the adoption of improved technologies by farmers. These technologies include the use of improved seeds, timely sowing, appropriate spacing, and timely weeding, harvesting, use of fertilizers for soil improvement as well as the use of minimum tillage.

Similarly, simulation models of the soil-crop-atmosphere system can help us advance our understanding of the mechanisms that determine crop responses while also forecasting crop performance in various geographies and decision-making systems. Crop simulation models are mathematical representations of how genetics, environment, and crop management interact to impact plant development processes. They have become a vital instrument in assisting scientific research, crop management, and policy analysis. Crop simulation models have been utilized for a variety of purposes in numerous countries throughout the world. Crop simulation models use projected or past meteorological data to estimate crop yields far in advance of harvest. Crop performance can also be predicted in regions where the crop has never been produced before or is grown under abnormal conditions. To validate the model, a minimal data set must be generated (RAMAWAT et al., 2012). Similarly, plant growth models require diurnal climatic data to forecast plant energy and water usage, photosynthesis rates, canopy temperatures, and evapotranspiration rates. Accurate evapotranspiration rate models will allow farmers to make real-time irrigation scheduling decisions (Matthew, 2022).

1.2. Statement of the Research Problem

Because of fast population increase, declining wealth, long-term climate change, and climate variability, Nigeria is frequently experiencing food shortages, famine, and water scarcity. Furthermore, with the typical annual crop grown in Nigeria being maize, numerous studies have indicated that the rise in temperature, fluctuating rainfall, droughts, and floods will have an impact on maize yield because Nigerian farmers rely heavily on rainfall for its production (Olomola & Nwafor, 2018; Otekunrin et al., 2019). Due to its heavy reliance on rain-fed agriculture and a number of uncertainties surrounding crop production's responses to climate change, Nigeria as an African nation is projected to be particularly vulnerable to the effects of climate change (Durodola & Mourad, 2020).

The recent escalation of food prices calls for sober reflection, owing to the fact that globe is facing a worsening food crisis period unseen in the last 30 years. In Kano state majority of the rural dwellers are predominantly agrarians but still food security is not grantee. Climate change has already begun to affect agricultural activities and consequently livelihoods of the population and their ability to support their family’s nutritional needs.

Similarly, agricultural system in Kano State depends largely on natural rainfall as the main source of crop production, and thus, exposed to spatial and temporal variability of the climatic parameters of rainfall and temperature, whose distribution is critical in affecting crop growth and its production. At the same time, maize needs a regular supply of water and does not tolerate drought. It requires rainfall of about 600-1,200mm per annum and this must be well distributed throughout the year. Additionally, maize requires an average temperature of 13-40°c and does not grow at higher temperatures. The most suitable soil for Maize must be deep, well drained and have favourable physical properties, an optimal moisture regime, sufficient and balanced quantities of plant nutrients and chemical properties. A pH of 5.5-7.5 is best for its production (Durodola & Mourad, 2020; Kogo et al., 2019). Thus, with the high dependence on rainfed agriculture and the uncertainties surrounding climate change and variability in the State, this study will conduct an assessment of climatic parameters that might influence and/or affect maize yield. Recommendations that will prove crucial to tackle the impacts of the changing climate on maize yield will be provided.

1.3. Research Objectives

Main Objective:

To analyse current trends of temperature and precipitation in relation to maize, and to simulate/model the impacts of these parameters on future maize yield in Kano State, Nigeria.

Specific Objectives:

1. To analyse the spatiotemporal trends of temperature and precipitation over 10 years in Kano State, Nigeria.
2. To evaluate the relationship that exists between climatic variables and maize yield in Kano State, Nigeria.
3. To simulate maize yield under different climate scenarios in Kano State, Nigeria.

1.4. Research Questions

1. How is temperature and precipitation spatially and temporally distributed between 2011 to 2020 in Kano State, Nigeria?

2. To what extent is the relationship between climatic variables and maize yield in Kano State, Nigeria?

3. How will maize yield be simulated under different climate scenarios in Kano State, Nigeria?

1.5. Relevance of the Study

Maize has a great potential of higher yield and one of the most populous cereal crops under cultivation, and if managed properly, it can go a long way in increasing food security through increased production in Nigeria. Modelling crop productivity and the impacts of climate change has always been a centre point for decision making and sustainable management of the agricultural sector in most African countries. However, while other studies focus on maize production, this study will focus on maize yield as a crucial milestone for enhanced food security in the future. The study is relevant as a stand-alone to be conducted in the study area fully incorporating the main drivers of climatic variables affecting crop yield. Moreover, this study focuses on the recent CMIP6 SSP scenarios for future projections. Since the study area has a large percentage of smallholder farmers, socioeconomic pathways need to be considered for decision makers to know the root cause of the problem and advice local farmers to adopt new and climate-smart agricultural techniques necessary for improvement of food production to address the Sustainable Development Goal of Zero Hunger and End Poverty.

CHAPTER TWO

2.0. LITERATURE REVIEW

This chapter elaborates on; climate history, future climate projections and their effects on maize yield, climate variability and maize yield, the main impacts of climate change/variability on crop productivity and yields, spatiotemporal analysis of temperature and precipitation coupled with trend analysis over a timespan of ten years and how impactful they are on the yield of maize in the study area, a simple linear regression analysis of climate parameters as independent variables against maize yield as dependent variable and lastly crop simulation model and future forecast of maize was also reviewed. Patterns and trends that emerge from different literature was analysed in order to primarily highlight the gaps in the existing literature and make a case for the significance of my research.

2.1. Climate History

The world's climate is undergoing unprecedented changes, surpassing anything seen in recent human history. Over the past few decades, these changes have had significant effects on both natural and human systems across the globe. The impacts are a result of observed climate change, regardless of its cause, highlighting the vulnerability of natural and human systems to these changes. The evidence for observed climate change impacts is particularly strong and comprehensive in natural systems. In numerous regions, alterations in precipitation patterns and the melting of snow and ice are modifying hydrological systems, thereby impacting water resources in terms of both quantity and quality. Ongoing climate change has prompted many terrestrial, freshwater, and marine species to shift their geographic ranges, change their seasonal activities, alter migration patterns, affect species abundances, and modify species interactions with very high effect. Climate change has also been linked to certain impacts on human systems, with the ability to differentiate between major or minor contributions from climate change and other factors. Numerous studies covering various regions and crops have demonstrated that climate change has more frequently resulted in negative impacts on crop yields compared to positive impacts. Since around 1950, changes have been observed in numerous extreme weather and climate events. Some of these changes have been attributed to human influences, such as a decrease in extremely cold temperatures, an increase in extremely warm temperatures, a rise in extreme high sea levels, and a greater frequency of heavy precipitation events in certain regions.(Halliru, 2013; IPCC, 2014b).

2.2. Future Climate Projections and their effects on crop yield

Future projections have shown surface temperature to increase throughout the 21st century in all evaluated emission scenarios. It is highly likely that there will be a higher frequency and duration of heat waves, as well as more intense and frequent extreme precipitation events in many areas. The ocean will continue to warm and become more acidic, leading to a rise in the global mean sea level. Climate change is anticipated to have a negative impact on food security. Without adaptation measures, the production of wheat, rice, and maize in tropical and temperate regions is projected to decrease with local temperature increases of 2°C or higher compared to the late 20th century levels, although some specific locations may experience positive effects (moderate confidence). If global temperatures rise by approximately 4°C or more above late 20th century levels, combined with increasing food demand, there would be significant risks to food security worldwide. The summary of projected changes in crop yields (primarily wheat, maize, rice, and soy) due to climate change during the 21st century indicates the percentage of projections showing increases versus decreases in yield. The data, based on 1090 data points, includes different emission scenarios, covers tropical and temperate regions, and encompasses both adaptation and no-adaptation scenarios (IPCC, 2014b). In (Sultan et al., 2014), the study found that there would be significant temperature increases in the entire West African sub region by 2050. These temperature changes have the potential to affect not only the hydrology of the region's climate, but also the behaviour of crops. For instance, higher temperatures could speed up crop growth, shorten their life cycles, and increase crop respiration. These changes would ultimately lead to a decrease in crop yields. Consequently, the anticipated shifts in weather patterns pose challenges to the livelihoods of farmers. Therefore, it is necessary to evaluate the impact of the projected climate on crop productivity in order to develop appropriate adaptation strategies.

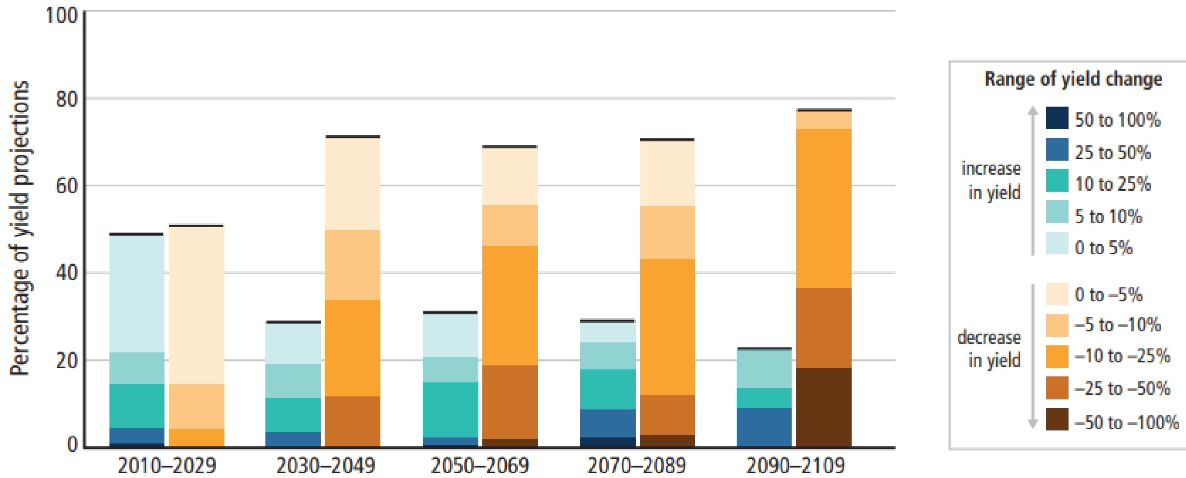


Figure 2: Summary of projected changes in crop yields due to climate change over the 21st century. Source: IPCC, 2014

2.3. Climate Variability and Crop Production/Yield

The changing climate has the potential to alter the amount of rainfall received in a region, leading to fluctuations within and between seasons. The distribution of rainfall within a particular season can have a more significant impact than changes in the overall annual rainfall. Furthermore, insufficient rainfall and unfavourable distribution, often caused by dry spells within a season, can result in drought conditions. These dry periods occurring during critical developmental stages of crops can adversely affect their yield, both in terms of quality and quantity. Similarly, rainfall availability which is the primary source of soil moisture, is considered to be of utmost importance in determining crop production. Additionally, elevated temperatures can induce stress during important reproductive phases, such as anthesis, leading to issues like anther dehiscence and pollen shedding. If temperatures surpass the tolerance levels of plants, it can have significant repercussions on their growth and, consequently, on crop yield (Halliru, 2013). The variability of climate has a significant impact on the output of rain-fed subsistence crops. Rainfall and temperature are crucial climate factors that influence the growth, development, and yield of crops. The effects of climate variability on agriculture are complex and diverse, with both direct and indirect consequences for the sector. These effects have a direct impact on agricultural systems through changes in precipitation patterns and temperatures, which can alter agro-climatic conditions, disrupt growing seasons, and affect the timing of planting and harvesting. They can also impact water availability and contribute to changes in pest, weed, and disease populations. The negative effects of climatic variability on food crop production include reduced output due to droughts, floods, and limited water availability. Decreasing rainfall and rising temperatures are particularly affecting crop production in rain-fed agriculture, exacerbating food insecurity. Climate variability and extreme events such as floods, droughts, heatwaves, and heavy rainstorms have global implications for crop production. Uncertainty in rainfall remains a significant challenge, particularly for smallholder farmers. Unpredictable rainfall has detrimental effects on food crop agriculture and can also lead to soil erosion, further impacting crop yields in rain-fed small-scale farming(Asfaw et al., 2018; Chisanga, C. B., Phiri, E., Chinene, V. R., & Chabala, 2020; Cline W. R., 2008; Glotter, M., Elliott, J., McInerney, D., Best, N., Foster, I., & Moyer, 2014; Guan K, Sultan B, Biasutti M & DB, 2017; Kamara et al., 2023; Kothiyal et al., 2023; Maina & Liman, 2020; Nneji et al., 2019; Shiru et al., 2020; Sultan, B.; Guan, K.; Kouressy, M.; Biasutti, M.; Piani, C.; Hammer, G.; McLean, G.; Lobell, 2014; Sultan B, Roudier P, 2013; Tofa et al., 2021; Yasin et al., 2022).

2.4. Climate Change Impacts on Crops Productivity and Yield

Climate change is a worldwide incidence, characterized by diverse indicators and impacts that vary across different regions. Over the centuries, climate change has become one of the greatest problems affecting almost all countries of the world with more deadly consequences in developing countries. Developing countries, which heavily rely on economic sectors influenced by climate conditions, are particularly vulnerable to the impacts of climate change. More importantly, its effects are caused by human activities that escalated after the industrial revolution through the increase of Greenhouse Gases Emissions into the atmosphere, causing global warming and leading to extreme climatic events, the most problematic being drought and flood, having direct linkage to agriculture and food security(Maïga et al., 2021; Wang et al., 2018). The agricultural sector is extremely susceptible to the effects of climate change. A simple 2°C rise in average temperatures has the potential to disrupt existing agricultural systems. Climate change has the capacity to significantly alter food production, including the methods, productivity, and overall patterns of crops, livestock, forestry, aquaculture, and fisheries (Cline W. R., 2008). The achievement of increased food grain production relies on the careful and efficient utilization of resources. Factors such as soil quality, climate conditions, crop varieties, and management practices play crucial roles in determining how crops respond to irrigation, fertilizers, and other inputs. Developing appropriate crop management strategies such as Diversification, crop rotation, monitoring and forecasting, integrated pest management and adaptive research and innovation while taking into account the uncertainties associated with weather patterns and resource availability, conveys significant economic and environmental implications (RAMAWAT et al., 2012). Reports such as that of IPCC showed that, agriculture is highly sensitive to climate change. A slight increase in average temperature could destabilize the entire agri-food chain and system. This would be evident in food production transformation, crops productivity and yield, change in planting season and patterns of operation among others. As IPCC asserts, the global production systems currently are largely vulnerable to climate change (IPCC, 2014b). These changes are expected to lead to decrease in crop production and therefore pose a threat to food security especially in arid and semi-arid dry climatic zones (Rahman MH, 2019). Temperature increases and erratic rainfall patterns are the major drivers having adverse impacts on crops' growth, yield and development in the drier regions. (Abbas G, 2017; Ahmad I, 2019). In climate change studies related to crop production systems, the most crucial aspect is the variation observed in climatic projections. These variations encompass long-term shifts in temperature, changes in the distribution of rainfall, increasing levels of CO2 and other atmospheric gases, as well as an increase in the occurrence of extreme weather events (IPCC, 2021). The changing climate has significantly affected crop production and yields, resulting in challenges to global and local food security. This impact is particularly pronounced in African countries where the prevailing agricultural system relies heavily on rainfall, making it highly vulnerable to changes in climatic conditions. Consequently, the agricultural sector in these regions exhibits a relatively high sensitivity to the effects of climate change (Guan K, Sultan B, Biasutti M & DB, 2017; Sultan B, Roudier P, 2013). The vulnerability of this sector is related to the increase in temperature and decrease in rainfall. As (Ravindranath NH, 2003) asserts, that in some areas around the tropics and subtropics, crop productivity is projected to either increase or decrease as a result of climate change. Several studies have been conducted worldwide in response to how some climatic variables, crop managements or farming practices affect the productivity or yield of some major staple crops. Similarly, numerous simulations and models were used to assess the impact of climate change on crops yield and productivity in Nigeria, African continent and the world at large. A review conducted by Wang et al on the effect of climate change on the yield of cereal crops, indicated that average global temperature is projected to rise in the near future due to high increase in GHGs' release to the atmosphere, causing reduction in agricultural yields hence food insecurity.

However, the agricultural activities are part of the major contributors of these gases' emission into the atmosphere, therefore, potential solutions for lessening the influence of climate change on crop productivity were discussed in the paper (Wang et al., 2018). Similarly, there are other studies that assesses and analyses the impacts of climate change on cereal/crop production using different modelling approaches. (Chandio et al., 2022) examine climate change impacts alongside carbon dioxide, financial development, energy consumption and rural labour force as crucial determinants of cereal production in Bangladesh by using auto-regressive distributive lag (ARDL) model to validate the long and short-term cointegration of the variables. The results of the findings confirmed a long-term connection among the tested variables, with some variables showing increase while others having significant negative impact on cereal production. (Yang et al., 2015) on the other hand investigates the impacts of climate change on northern limits and crop planting areas after assessing rising temperatures to have dramatic effect on multiple cropping systems in China, hence the need to estimate the impacts of the change in the crop planting areas of multiple cropping systems in China's crop production. The study used APSIM model to evaluate historical and simulated crop yield between 2011 – 2100 to quantify the crop production in China. The results showed that northern limits of multiple cropping systems have shifted northward and the projected area of cultivated land triple-cropping system may be significantly expanded in the 21st century. The study concludes that warming due to climate change may cause a positive impact on crop production in China. Correspondingly, some studies assesses the impacts of climate change on maize production. (Yasin et al., 2022) conducted a field experiment in semi-arid region of Pakistan using a multi-model approach to assess the impacts and uncertainties of climate change on maize crop, in which the results predicted a rise in temperature from 1.57 to 3.29 degrees Celsius during maize growing season under RCP 8.5 when compared to the baseline. Similarly, CERES-Maize and APSIM model indicated lower root mean square error values than CSM-IXIM-Maize model. The study concludes that maize crop may face a high yield decline that could be mitigated by changing the sowing dates and fertilizer application. In assessing impact of climate change on crop production with closer look on uncertainties of climate projections and crop model parameters, (Zhang et al., 2017) used 24 climate projections with eight GCMs and three emission scenarios, RCP 2.6, 4.5 and 8.5 to check the climate projection uncertainty, while two crop models with a hundred parameters in each model was employed to check the crop model uncertainty. This study was conducted to evaluate the impact of climate change on maize (Zea mays L.) yield at three different locations in Northeast China and the multi-model ensembles was the best method to deal with the uncertainties. The results of the simulations indicated 5% reduction in maize yield in future periods as compared to baseline. Similarly, the results showed that the uncertainty from climate projections was larger than the contribution of the crop model parameters. In West and Sub-Saharan Africa, a number of studies on the impact of climate change on crop yields have previously been carried out, among them exist some studies with an evidence of projected climate change impact on agriculture, crop productivity and yield, since crop production in most parts of the regions proved to be rain-fed. The studies reviewed and assessed the projected climate change scenarios and its variation on the productivity of cereals in smallholder settings, maize growing regions of Africa and sources of uncertainty as well as negative impacts from temperature increase relative to change in precipitation. A negative impact on crop and cereal productivity showed an increase in severity with intensification of temperature rise and warming as projected by some climate models and some RCPs, thereby highlighting the role carbon fertilization effect as well as unsustainable agricultural development pathway will have on crop yields under major CO_2 concentration scenarios and also on agricultural production systems with less emphasis on soil conservation sustainable pathways in West Africa. Previous literature has highlighted that West Africa has been undergoing rapid climate change, characterized by rising temperatures and an increase in extreme weather events. These changes are anticipated to have detrimental effects on crop yields, resulting in losses in agricultural productivity in the region (Cairns et al., 2013; Maccarthy et al., 2021; Roudier et al., 2011). A further instance of the impact of climate change on cereal crops yield and production can be seen in different other studies conducted in some nations in the continent. Msowoya et al., used fifteen GCM ensembles under SRA1B and SRB1 emission scenarios to predict long-term changes in climate variables which were compared to a baseline period to investigate climate change effects on maize as a staple crop in Lilongwe district, Malawi. Results showed that rainfed maize production may decrease to 14% by mid-century which is projected to 33% decrease by far future (end of the century). They concluded that adaptation strategies be improved to boost Malawi's food production and stability (Msowoya et al., 2016). In another study conducted in Zambia, five GCMs and WOFOST crop model were used to assess climate change impacts on maize yields under RCP 4.5 and 8.5 scenarios. The results indicated significant increase in surface temperature and warm days, accompanied by reduced precipitation throughout most part of the country. The decrease in rainfall indicates shorter growing season and a threat to crop yields. Maize yields are expected to decline by 15 to 20% in the near future and 20 to 40% in the far future due to rise in temperature. The importance of improved nutrient management for enhancing maize production in Zambia was highlighted(Siatwiinda et al., 2021). Due to its heavy reliance on rain-fed agriculture and a number of uncertainties surrounding crop production's responses to climate change, Nigeria as an African nation is projected to be particularly vulnerable to the effects of climate change (Durodola & Mourad, 2020). Similarly, several studies considered other factors than climate change to have impact on crop production in Nigeria. These factors ranges from; contract farming(NAZİFİ et al., 2021), fertilizer treatment and use of nitrogen and phosphorous fertilization as crop management option(Aliyu, A.U., Yusuf, M.A. and Buba, 2022; Tofa et al., 2023), and economic analysis of maize production in the country(Onuk E. G.; Ogara I. M.; Yahaya H.; Nannim N., 2010). On the other hand, studies characterizing the changes in crop yields in response to climate change impacts were also numerous in Nigeria. (Adejuwon, 2006) used incremental scenarios to assess the response of crop yields such as maize, sorghum and rice to changes in various climatic elements such as rainfall, relative humidity, temperature, solar radiation and CO2 concentration. The results showed high probability increase in crop yield in the first part of the 21st century with a projected decrease in the second part. The results of the previous study showing increase in near century looks similar to (Tofa et al., 2021) but with major focus on using DSSAT to quantify the impact of climate change on maize yield and the potential benefits of the use of drought-tolerant maize variety in savanna ecological zones of Nigeria under RCP 4.5 and 8.5. Their results showed 1 – 6% less reduction in yield when drought-tolerant variety were used, hence the need for modification in maize breeding scheme to combine tolerances to drought and heat stress. Narrowing down to Kano State, Nigeria, a study conducted by (Adamu et al., 2021) centred on climate variability impacts on cereal crop yields in Wudil local government area of Kano state. Regression analysis was used to correlate the impacts of climatic variables as independent variables on sorghum, maize and millet as dependent variables. The obtained results indicated climatic elements to have moderate impacts on crop yields based on regression coefficient of determination. Even though, rainfall was the most influential while evapotranspiration was the least according to the indices of standardized coefficients. Thus, water saving technologies and irrigation farming system was recommended by the researchers. Similarly, (Maina & Liman, 2020) used primary field and secondary data to simulate future effect of climate change on maize yield using APSIM model. Results showed significant relationship between simulated and observed yield. Moreover, the result also indicates Kano to have warmed up under the baseline by 0.4870C, hence resulting in yield decline from the base. The future yield also showed effect on maize grain as a result of temperature rise and rainfall variability, even though temperature showed more effect than precipitation. Lastly, the study recommends appropriate adaptation strategies to mitigate the impact of impending future climate change in Kano State.

2.5. Spatiotemporal Analysis and Trends of Temperature and Rainfall

Temperature and precipitation are some metrics widely considered by researchers in trying to understand anomalies of the climate system. Precipitation and temperature are fundamental variables in climate sciences and hydrology that are commonly used to assess the extent and magnitude of climate change and variability. In countries where the economy heavily relies on low-productivity rainfed agriculture, trends and fluctuations in rainfall are often cited as key factors contributing to various socioeconomic challenges, particularly food insecurity. Therefore, it is essential to investigate the spatiotemporal dynamics of these meteorological variables. Such research provides valuable insights for policymakers and practitioners, enabling them to make informed decisions based on the understanding of climate patterns and their implications on agriculture and food security. In countries where rainfed agriculture is predominant, exploring the spatiotemporal dynamics of meteorological variables in the context of changing climate is vital to assess climate-induced changes and suggest feasible adaptation strategies. By taking low rain gauge and meteorological stations into consideration, different studies have employed different datasets to conduct spatiotemporal analysis of some climatic variables. Even though focusing on seasonal and annual variability and trend of temperature and rainfall based on observed data might prove futile. Gridded satellite data are readily available and they enable a researcher to overcome the problem of missing data which is common in observational data(IPCC, 2007).

Previous studies on spatial and temporal analysis of temperature and rainfall can be found at individual countries or sub-regions(Aswad et al., 2020; Murata et al., 2014; Yue & Hashino, 2003; Zacatecas, 2020). The alterations in the temporal and spatial patterns of rainfall in Africa have had negative impacts on agriculture and food production among farming communities. These effects are direct, as they lead to changes in agro-ecological conditions, and indirect, as they influence the growth and distribution of incomes and the demand for agricultural products. As a result, the agricultural sector and the livelihoods of farming communities have been significantly affected by these changes in rainfall distribution. Global warming effect in all regions, increase in temperature and decrease in total annual precipitation are the most significant results found in a long-term analysis of rainfall and temperature between 1950 to 2013 in Burkina Faso. Linear regression modelling was used for the trends coefficients which allowed easier comparison of significance levels of all the chosen indices(Longueville et al., 2015). However, in terms of global climate changes, (Gönençgil, 2012) identified and explained the trends of average precipitation, average minimum and maximum temperatures between 1975 to 2011 in the Thrace. Mann-Kendall rank correlation test was used and results obtained indicated that temperature and precipitation trends were associated with global processes and a general increase in annual average minimum and maximum temperatures in July with decreasing trend in annual precipitation levels which started in 1975 and eventually escalated in the 90s. In Wainganga River basin of Central India, gridded rainfall data was analysed to observe long term spatial and temporal trends on annual and seasonal scales between 1901 to 2012. Mann-Kendall test was used to detect the trends, ArcGIS for spatial patterns while Sen's slope estimator was used for magnitude of change over time. Most of the grid points showed a decrease in annual rainfall trends but in seasonal trend analysis, only post monsoon season showed a non-significant decreasing trend over the 112 years ago(Taxak et al., 2014).

2.6. Multiple Linear Regressions (MLR)

Multiple linear regression with principal components (MLR) is a method in statistics that scales down data, aiming to uncover a linear connection between a main variable (like maize yield) and several others (such as temperature, precipitation, and solar radiation). MLR helps to map out the link between large-scale data and local climate factors by fitting a straight-line equation to the observed information. Each point of the main data corresponds to a specific climate data point. Therefore, MLR assists in estimating the main variable (Y) values based on a set of independent variables (X1, X2, Xp). This analysis involves using principal components and fuzzy c-means clustering membership values. The following equations involving the seasonal components are used for regression analysis.

Yi =a+b1X1+b2X2+⋯+ bm Xm + C,

Where;

Yi is the dependent variable;

X1, X2, ..., Xm are the independent variables;

a is the intercept;

b1, b2, and bm are the multiple regression coefficients, to be estimated by the least-squares method and

C is the error term.

Even though using MLRs with climatic variables can result in multicollinearity issues, leading to misinterpretation of parameter estimation errors, this problem can be fixed by using principal components (PCs). PCs help by reducing the number of variables through transformations, thus eliminating multicollinearity among independent variables. As a result, the PCs of the explanatory variables create a new set of variables with the same information as the originals, but without correlation. In (Yahaya et al., 2020) the study analysed the relationship between climatic factors and sugarcane yield in Southern Adamawa state, Nigeria. Utilizing data from NiMet, GWDS, and NASA POWER spanning 35 years, they found weak positive correlations between sugarcane yield and minimum temperature, rainfall, and relative humidity, while weak negative correlations existed with maximum temperature and solar energy. This underscores the importance of considering weather trends and meteorological advice for successful sugarcane production.

In another study, (Mansour, 2022) investigates the correlation between weather conditions and crop production in Alabama. They utilize regression analysis to analyse the relationship between weather factors such as temperature, humidity, and precipitation, and the production of four major crops: cotton, soybean, peanut, and corn. To conduct the study, the researchers collect crop data from USDA-NASS and weather data from NASA-POWER for a period spanning 33 years (1988-2020). By using the R programming language, they analyse the collected data to identify correlations and fluctuations between weather conditions and crop production over the years. This approach allows them to assess the potential impact of climate factors on agricultural productivity and provide insights that could aid state leaders and farmers in protecting crops and increasing production.

2.7. Crop Modelling and Maize (*Zea mays* L.) Yield

Crop simulation models are mathematical depictions of how plants grow, considering factors like genetics, environment, and how crops are managed. They're crucial for research, managing crops, and analysing policies. By using anticipated or past weather data, these models can forecast crop yields long before harvesting. They can even predict how crops will perform in climates where they've never been grown or under abnormal conditions. With the growing concern over climate change, there's been increasing interest in using these models to understand how it affects crop productivity. Many global initiatives focus on modelling maize and other crops. (Chisanga, C. B., Phiri, E., Chinene, V. R., & Chabala, 2020). The preference on maize can be attributed to its significant role as a major staple cereal crop globally, serving both human consumption and livestock production(Sultan B, 2016). Maize (corn) needs just the right climate to grow well and stay healthy. If temperatures wander too far from ideal, especially if they are consistently high during the day and night, it can really upset the maize harvest. (Yasin et al., 2022). Maize (Zea mays) is a staple food for a large part of the population around the Globe and is of great socio-economic importance in the Sub-Saharan Africa (FAO, 2013). It is one of the most heavily cultivated cereal crop globally, and one of the main cereal crops of West Africa and the most important cereal food in Nigeria (Onuk E. G.; Ogara I. M.; Yahaya H.; Nannim N., 2010). In order to grow, maize needs soils that are deep, medium-textured, well-drained, fertile, and have a pH range of 5.5 to 8.0. Since the majority of farmers in the nation adopt rain-fed agriculture, abnormalities in the onset, frequency, and intensities of rainfall are another issue threatening maize output in the nation. Maize cultivation is getting increasingly challenging as a result of crop output and climatic uncertainty. Low maize yields have a significant impact on the food security and income of smallholder farmers throughout the nation and in the study area(Durodola & Mourad, 2020). In fact, maize output in Nigeria's savannas, notably the semi-arid Sudan savanna zone, has expanded dramatically during the last three decades (IITA, 2017). With growing population and increase demand for food, maize has advanced from a backyard crop, primarily grown by women and children, to a significant commercial commodity producing food, animal feed, and industrial raw materials (Adnan et al., 2020). In Nigeria, maize (Zea mays L.) is one of the most significant cereal crops, providing both food and revenue to the citizens. Nigeria is Africa's second largest producer of maize, generating around 12 million metric tons from 7.5 million hectares in 2021 (FAOSTAT, 2022). The northern Nigerian savanna is the most favourable zone for maize cultivation in Nigeria because of its high incident solar radiation, enough rainfall, and minimal rates of biotic stressors (Shehu B.M, et al., 2019). However, despite decades of increased output, maize yields in the Nigerian savannas remain poor, with yields typically falling below 2 tha^{-1}, resulting in low total production and the need to import maize to meet yearly demand gaps of 4 million metric tons. According to (Tofa et al., 2021 & Dugje et al., 2006), poor soil quality, unpredictable weather patterns, drought, and attacks from Striga hermonthica are the main obstacles to growing maize successfully in Nigeria's savannas. Additionally, climate change poses a serious threat to maize yields in Nigeria, with rising temperatures and more frequent droughts expected to further decrease production in the future. Reports indicate that climate change is already impacting food production in the country, and these effects are likely to intensify. (Salako et al., 2021). In their work, Tofa et al. (2021) projected that temperatures in the Nigerian savannas will rise by 2.2 °C-2.9 °C by mid-century, and up to 3.9 °C-5.0 °C by the end of the century under the RCP8.5 scenario. The models also forecasted more rainfall in the drier Sudan savanna and less in the Guinea savannas. Moreover, the study found that by the end of the century, drought-tolerant maize yields in Nigeria's savannas will be reduced by 13% to 43%. Thus, maize production is adversely susceptible to extreme weather events due to climatic variability, even a previous report suggested that in the absence of adaptation strategies, climate change could result in crop yield losses of 30%–50% by 2020 and up to 90% by 2100, with a greater impact on maize crops in northern Nigeria (BNRCC, 2011). Therefore, to lessen the negative effects of climate change on maize, several adaption strategies have been proposed. This involves the adoption of better crop management strategies such as nitrogen fertilizer delivery, planting date manipulation, additional irrigation, and the deployment of drought-resistant cultivars (Asfew & Bedemo, 2022; Tofa et al., 2021, 2023).

Modelling crop production by considering varying meteorological factors enables the anticipation of corresponding changes in crop yield. These crop models are valuable for predicting the likely impacts of climate change on crop yield at various spatial and temporal scales(Glotter, M., Elliott, J., McInerney, D., Best, N., Foster, I., & Moyer, 2014). For example; (Bebeley et al., 2022) utilized NASA Power data, which includes daily minimum and maximum air temperatures, as well as daily solar radiation, sourced from the NASA database for Climatology Resource for Agro-climatology. This data was merged with downscaled CHIRPS rainfall data to create comprehensive weather datasets for Jagiri (one of the study locations). These datasets were then used as inputs for the

Cropping System Model (CSM)-CROPGRO-Soybean to evaluate the performance of three soybean varieties in the three Nigeria savannas viz; Sudan savanna, northern Guinea savanna and southern Guinea savanna and determine optimum sowing windows in them. Additionally, R scripts were created to append data for CHIRPS and NASA Power, and the weatherman utility software in the DSSAT v4.7 was used to input the weather data for the sites and check for errors before use.

Crop simulation and multi-linear regression models can be used to quantify the potential impacts of climate change on maize growth and yield under both rain-fed and irrigated conditions(Jiang, R., He, W., He, L., Yang, J. Y., Qian, B., Zhou, W., & He, 2021). Some of these models include AquaCrop, Agricultural Production Systems Simulator (APSIM), Decision Support System for Agro-technology Transfer (DSSAT), EPIC, CropSyst, Root Zone Water Quality Model (RZWQM2), SARRA-H, IMPACT+DSSAT, ALAMANC, WOFOST, ADEL, GEPIC, Empirical, MOS, GLAM-Maize, InfoCrop, and EcoCrop. The following studies used CERES-Maize model in simulating maize crop to project the yield and productivity (Kogo et al., 2019; Kothiyal et al., 2023; Lobell & Burke, 2010; Yasin et al., 2022). Furthermore, APSIM model, WOFOST, Aquacrop, DSSAT and EPIC were used by (Adejuwon, 2006; Durodola & Mourad, 2020; Kassie et al., 2015; Kourat et al., 2022; Maccarthy et al., 2021; Maina & Liman, 2020; Siatwiinda et al., 2021; Tofa et al., 2021; Yang et al., 2015) to project the impacts, effects and benefits of climate change, variability and water requirements on different crop's yield, productivity, growth or adaptability. The CERES-Maize model has also been used to assess the consequences of present and future climatic changes on crop yields and to evaluate alternative crop management practices as climate change adaptation measures (Tofa et al., 2021). The DSSAT-CSM is a collection of computer programmes and tools combined into a single software package to ease the use of crop simulation models in research and decision-making. The CERES-maize model is one of the maize growth simulation models in DSSAT that operates on a daily time step and is cultivar and site-specific. It dynamically simulates the development of roots, shoots, and final grain yield as a function of soil/weather conditions, crop management practices, and cultivar genetic coefficients of characteristics (Ritchie J T, Singh A, 1998). The model integrates mathematical equations to explain the fundamental flow and transformation processes of soil carbon, water, and nutrient balances on a daily or hourly basis (Adnan et al., 2020). It also forecasts the temporal variations in crop development, nitrogen absorption, water consumption, and ultimate yield, together with other plant, soil, and weather features and outputs. The CERES-Maize model requires the following basic input data: daily weather data (maximum and minimum temperature, precipitation, and solar radiation); soil data, which includes general site and soil surface information, soil profile characteristics (physical and chemical), and key levels of water availability at each soil layer for saturated water content (SAT), drained upper limit (DUL), lower limit (LL), and soil layer thickness; crop management data; and genotype-specific parameters (GSPs), or genetic inputs that characterize physiological processes and developmental variations across crop kinds (Hoogenboom G. et al., 2021).

Several studies employed different approaches, and obtained different results to assess climate change impact on cereals productivity or yield in different parts of the world. However, this study aims to assess the impacts of climate variability on maize yield by assessing the spatial and temporal distribution and trends in climatic variables of current and future temperature and precipitation using ArcGIS 10.8.2 version, regression analysis of climatic variables as independent variables and maize yield as dependent variable using simple linear regression model on XLSTAT alongside crop simulation model of the Decision Support System for Agrotechnology Transfer (DSSAT) which is a modelling framework that simulates vegetative and reproductive development, growth and yield of different cereals and legumes as a function of crop characteristics, weather and soil conditions, and crop management scenarios. The study opted for this integrated approach because it is more comprehensive and suitable to our objectives, and the adoption of CMIP6 SSP scenarios will prove helpful for providing insights into socioeconomic pathways and uncertainties of climate and crop models as well as means for developing alternative adaptation and mitigation strategies for smallholder farmers in the study area.

CHAPTER THREE

3.0. METHODOLOGY

3.1 Study Area

This research study area is Kano State, Nigeria, where maize production is predominant with large percentage of smallholder farmers. Kano State is situated between latitudes 10° 3' and 12° 37' N and longitudes 7° and 90° E(http://www.kanostate.net). Most of the land area lies within the Sudan vegetation zone, with the exception of the southern borders where guinea savanna predominates. Kano state has an arduous (tropical continental type) climate with relatively wide and rapid changes of temperature and humidity. During the months of December and January, the harmattan (dry northeast wind) is at its peak blowing thin dust over the state from the Sahara Desert. This dry harmattan winds carrying dust from the north increase the desiccation effect of high temperature during the long dry season(Halliru, 2013). As Northern Nigeria's commercial hub, its' overall land area of 20, 760 square kilometres, with 1,754,200 hectares of fertile agricultural land, of which 86,500 are solely Fadama land, with grazing lands also covering around 75,000 hectares (Irohibe & Agwu, 2014). The rainy season, which typically lasts from April to September with 134.4mm of annual precipitation, begins after the dry season, which typically lasts from October to April. The occurrence of peak rainfall, peak runoff, and peak discharge starts from beginning of July and August indicating highlights of the climatic parameters. Between 800 and 900 millimetres of rain on average per year fall in the area. Kano has exceptionally productive soils, which Olofin (2016) describes to be due to both effective user management practices and harmattan dust, which scatters minerals that enrich the soils. Because of the state's fertile soil, a variety of foods can be produced in large quantities(Tukur et al., 2018).

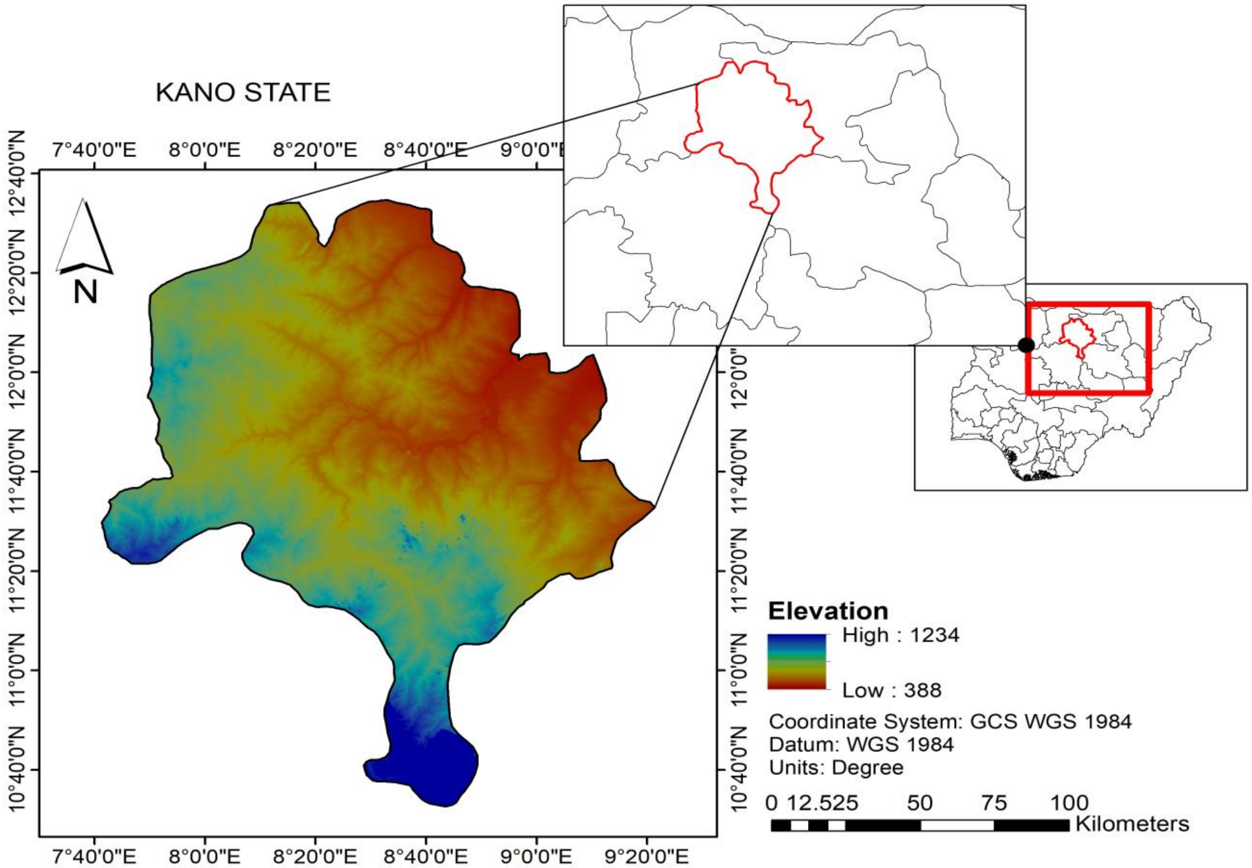


Figure 3: Location and Elevation of the study Area

3.2 Demographics

Kano state is one of the fastest growing regions in the whole of West African sub-continent. The state for the last three decades has been experiencing rapid economic and population growth. Kano city is the single most populous urban centre in northern Nigeria and is ranked next to Lagos State and Ibadan in the Nigerian Federation(Adamu Mustapha et al., 2014). Kano State is ranked 2nd most populous in Nigeria. According to United Nations (UN) Kano State, Nigeria statistics 2022, Kano State population amounts to 11,151,624 as at 2022, with a projection of about 20,647,647 by 2050. And 75% of the populace are into agriculture (NPC, 2007). Maize is grown in many parts of Nigeria but the northern part dominates all other regions with Kano and Kaduna States taking higher percentages(NAZİFİ et al., 2021). Murphy, (2010) indicated that growing maize by smallholder farmers can overcome food insecurity in their households. These smallholder farmers make up to 80% of farmers in Northern Nigeria, and they produced substantial percentage of food consumed by Nigerians particularly maize crop. Furthermore, maize cultivation is getting increasingly challenging as a result of crop output and climatic uncertainty (Durodola & Mourad, 2020).

3.3 Materials/ Data sources

For this study, multiple approaches were used to assess the impacts of climate change on maize yield in Kano State. Rainfall and temperature data for spatial-temporal variability and trend analysis have been obtained from different sources. Similarly, crop, weather and soil data for regression and crop simulation were gotten from multiple sources viz;

3.3.1. Modern Era Retrospective-Analysis for Research and Applications (MERRA-2)

Temperature data for spatiotemporal analysis from 2011 to 2020 was downloaded from MERRA 2 Native Resolution monthly and annual data with the NASA Langley Research Centre (LaRC) website (https://power.larc.nasa.gov/) considering eight (8) stations (Lat. Long. 12.27-7.86; 12.53-8.28; 12.25-8.87; 11.90-9.14; 11.87-8.52; 11.52-7.77; 11.25-8.70 and 10.71-8.71 respectively). Due to various climatic and environmental conditions that might hinder obtaining accurate ground numerical data for different analysis, data for such applications can be collected from remotely sensed satellite data and over a long time for various locations. The National Aeronautics and Space Administration (NASA) provides a resources base for such data. The NASA through its Earth Science research program, has long supported satellite systems and research providing data important to the study of climate and climate processes. These data include long-term climatologically averaged estimates of meteorological quantities and surface solar energy fluxes. Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) data spans the time period from 1981 to within several months of real time. The meteorological parameters are based upon the MERRA-2 assimilation model. The data/parameters in NASA power are provided on a global grid with a spatial resolution of 0.5◦ latitude by 0.5◦ longitude. Various meteorological variables, such as maximum and minimum temperatures, radiation, albedo, relative humidity, and precipitation, were sourced from the Power Data Access viewer of the National Aeronautics and Space Administration. Several studies have used NASA POWER data in their analysis, either in conjunction with another dataset or as a standalone. NASA power data can be utilised to assess its reliability in providing long-term rainfall and temperature data for areas where observed data is not readily available(Gunaratne M.D.N, De Silva S.H.N.P, 2022), to evaluate drought events in arid and semiarid locations(Rasool et al., 2021), to estimate and compare diurnal variations of meteorological parameters(Matthew, 2022) or to analyse the relationship between climatic factors and crop yields (Yahaya et al., 2020; Alli, A. A and Omofunmi, 2020) among others.

3.3.2. CRU and CHIRPS

Considering the low rain gauge station density over the study area, rainfall data for spatiotemporal analysis was downloaded from both Climatic Research Unit version 4.06 (CRU v4.06) and Climate Hazard Group Infrared Precipitation with Station Data (CHIRPS).

The Climatic Research Unit gridded Time Series (CRU TS) is a widely used climate dataset on a 0.5` latitude by 0.5` longitude grid over the whole world except Antarctica. The dataset is a regularly updated high-resolution monthly grid of land observations from multiple sources covering ten variables from 1901 to present (Harris et al., 2020). The gridded data are a reconstructed data series based on records of gauge stations and meteorological satellite observations. The gridded data set is very useful in view of the fact that weather stations are limited in number, unevenly distributed, have a missing data problem and a short period of observation and the trends displayed are stronger and more widespread than others, they are used in several researches to perform different analysis(Asfaw et al., 2018; Harris et al., 2020; Ongoma & Chen, 2017).

The Climate Hazard Group Infrared Precipitation with Station Data (CHIRPS) is a new quasi-global (50°S-50°N), high resolution (0.05°), daily and monthly precipitation dataset. CHIRPS uses a 'smart interpolation' approach, working with anomalies from a high-resolution climatology. The CHIRPS station blending procedure is a modified inverse distance weighting algorithm that has several unique characteristics among which is the use of the CHIRP to define a local decorrelation distance. The CHIRPS data products are derived using approximately 12,000 lines of code written in the Interactive Data Language which is not restricted, and is available upon request. CHIRPS data are provided in NetCDF, GeoTiff, and Esri BIL formats. The units are in "mm" per time period(Funk et al., 2015).

3.3.3. WorldClim

In order to determine future climatic conditions through analysing spatial extent for the study area, temperature and precipitation data was downloaded from the WorldClim website (https://worldclim.org/data/index.html) from 2041 to 2060 as near future and 2081 to 2100 as far future. These metrics (temperature and precipitation) were chosen as they best define climatic characteristics of the study area. Three GCMs were selected as per their appropriateness in projecting rainfall and temperature(Shiru et al., 2020). These are; MIROC 6(Japan Agency for Marine, Earth Science and Technology), HadGEM3 (Met Office Hadley Centre, UK) and MRI-ESM2 (Meteorological Research Institute). Similarly, two scenarios from Shared Socioeconomic Pathways SSP5,8.5 and SSP2,4.5 of the Coupled Model Intercomparison Project 6 (CMIP6) were chosen for this analysis of future climatic spatial distribution. CMIP is a framework for climate model experiments, allowing scientists to analyse, compare and improve GCMs in a systematic way. Scenarios are a crucial component of climate change research and evaluation. They help us comprehend the long-term effects of short-term choices and allow academics to investigate several conceivable futures in the context of fundamental future uncertainty. Perhaps most crucially, scenarios have historically been critical for achieving integration across diverse research groups, for example, by offering a common foundation for the examination of mitigation strategies, effects, adaptation alternatives, and physical earth system changes. Therefore, CMIP6 scenarios were chosen because higher climate sensitivity is more prevalent in their model versions (Arias, P.A., N. Bellouin, E. Coppola, R.G. Jones, G. Krinner, J. Marotzke, V. Naik, M.D. Palmer, G.-K. Plattner et al., 2021). The SSPs were created to give five potential pathways for future socioeconomic changes that may occur in the absence of explicit new policies and initiatives to minimize climatic forcing or improve adaptive capability. SSP2,4.5 was considered because it is the scenario with medium challenges to mitigation and adaptation while SSP5,8.5 as the scenario with high challenges to mitigation, low challenges to adaptation(Riahi et al., 2017).

WorldClim is a database of high spatial resolution gridded global weather and climate data for historical (near current) and future conditions that can be used for mapping and spatial modelling (WorldClim, 2022). Previous studies have concluded that WorldClim datasets are accurate, reliable, valuable and highly useful in climatic evaluations and predictions (Eneanya et al., 2018; Ishoro et al., 2023; Nneji et al., 2019; Poggio et al., 2018; Salako et al., 2021).

3.3.4. Data for Regression and Crop Simulation

Maize yield data and ground in situ weather data for regression analysis was obtained from the Kano State Agricultural and Rural Development Authority (KNARDA), International Institute for Tropical Agriculture (IITA), Kano State University of Science and Technology (KUST) and

Bayero University Kano (BUK) meteorological stations respectively. KNARDA is a government organization located in Kano State, Nigeria and is in charge of directing state-wide agricultural and rural development initiatives. The IITA is a non-profit international organization founded to assure food security for some of the world's poorest people and provide them with viable strategies that could create real, long-term results for economic development and community stability. KUST and BUK are state and federal universities located in the study area.

Maize yield and rainfall data from 2011 to 2020 were obtained from KNARDAs' Technical Service Department as well as IITAs' meteorological stations. Similarly, temperature data from 2011 to 2020 was obtained from KUST and BUK weather stations respectively.

Weather, soil and maize yield data for calibration of the DSSAT model was obtained from a field experiment conducted in 2014 at an experimental farm site located within the vicinity of Bayero University, Kano. While, data for validation was obtained from CIMMYT Tamasa Project conducted in 2015 and 2016 at three different locations in the study area.

3.4 Methods

3.4.1 Climate Parameters

Historical meteorological data from 2011 to 2020 were used to observe the spatiotemporal extent of climate parameters of temperature and precipitation in the study area. For this study, Remote Sensing (RS) and Geographical Information System' (GIS) data was used for generating spatial maps. GIS software plays a crucial role in environmental studies and varies from other computerized systems like spreadsheets, word processors, and database management systems by specifically processing and managing spatial data. Spatial data refers to observations and measurements of attributes or properties within a geographical space during a particular time period. ArcGIS developed by ESRI (http://www.esri.com/) and widely used since the 1980s, is one of the comprehensive collections of GIS software products and is used for analysis in this study (Medeiros & Pires, 1994; Zhu, 2016). Maximum/minimum temperature and precipitation as the major climate parameters for assessing historical climate impacts were selected. Annual mean maximum and minimum temperatures and annual sum precipitation were imported into ArcGIS version 10.8.2 and using the Inverse Distance Weighted (IDW) interpolation tool, spatial maps of the study area were generated for analysis of the historical spatial distribution of temperature and precipitation from 2011 to 2020.

3.4.2 Future Climate Scenarios

The CMIP6 retrieved data was used for future scenarios analysis. SSP2,4.5 and SSP5,8.5 were the two emission trajectory predictions that were chosen for the future spatial analysis. With the use of these multi-model ensembles, we were able to generate spatial maps in the future while taking into account both parametric and climatic uncertainties of temperature and precipitation. For the calibration of the DSSAT model, the same dataset was used for the future prediction of maize yield projection under the two emission scenarios. During the calibration, the downscaled parameters from the GCM which acted as the predictors were used iteratively to select the best variables for the temperature and precipitation. For ease of graphing and representation, the final outputs were exported to excel software.

3.4.3 Man-Kendall Test and Sen.'s slope

The data collected over the period were analysed using Man-Kendall's non-parametric tests. Prior studies showed that the non-parametric Mann-Kendall test is the most widely used test and several researchers have adopted this approach to understand the trends in the temperature and precipitation parameters(Aswad et al., 2020; Kamal & Pachauri, 2018) For rainfall trends, Aswad et al., 2020 used the same to understand monthly and annual rainfall trend in Sinjar District, Iraq.
For this study the Mann-Kendall (non-parametric) test was performed to determine if there were upwards, downwards, or no trends in the temperature and rainfall trends in the study area. And for this data set the formula is provided by the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i)$$

Where:

n: numbers of data points

x_j and x_i are annual values in years j and i, j > 1

And Sign (x_j–x_i) calculated using the equation:

$$sign\left(x_j - x_i\right) = \begin{cases} -1\ if\ \left(x_j - x_i\right) < 0 \\ 0\ if\ \left(x_j - x_i\right) = 0 \\ +1\ if\ \left(x_j - x_i\right) > 0 \end{cases}$$

The Sen.’s slope estimator can also be used to determine the strength of a trend. It is discovered that the Sen. (1968) slope estimator is an effective tool for developing linear relationships. Sen.'s slope was a very important tool over regression's slope because it is less affected by large data series errors and outliers. The mean of all pair-wise slopes for every pair of points in the dataset was found to represent the slope of the Sen.(Aswad et al., 2020). This test was originally developed in 1968 for the performance of checking the statistical trend of different variables. However, in recent times in climate change studies (Durodola & Mourad, 2020) have adopted it in their studies. In this study however, the test was also used for checking the performance of each of the variables’ trend were the R2 and RMSE significance were analysed.

3.4.4. Multiple Linear Regression (MLR)

Using multiple linear regression model, the temperature and precipitation as independent variables were evaluated to determine whether they have any significant effect on maize yield as the dependent variable in the study area over the past 10 years. A linear regression analysis is a parametric tool and one of the most widely used methods to detect a pattern in data series(Aswad et al., 2020; Lobell & Burke, 2010). For this study regression analysis was used to determine the impacts of climatic elements such as; rainfall and temperature, as the independent variables, and the maize yield as the dependent variable. Furthermore, the multiple linear regression was done to determine which climatic variable has more effects on the crop yield in the study area.

3.4.5. DSSAT Calibration and Validation

The DSSAT model was evaluated with experimental data collected during two field experiments conducted in Kano in the year 2014 and 2015. For calibration of the model, data from an experiment conducted in a farm site in Bayero University, Kano in the year 2014 together with soil data and weather data of the experimental site were imported into the DSSAT version 4.8.2. For validation, similar data from an experiment conducted in 2015 in Kano at three different locations was used, coupled with soil data from the same locations. However, weather data from NASA power was used to validate the model sensitivity analysis.

CHAPTER FOUR

4.0. RESULTS AND DISCUSSIONS

4.1. Spatial Analysis and Trends of Historical and Future Temperature and Precipitation Distribution in Kano

4.1.1. Observed Spatial Precipitation

Table 4.1 presented the magnitude of seasonal and annual precipitation patterns obtained from the Mann-Kendall test and the slope estimator from Sen. From the table, there are weak to moderate positive associations between the variables for each season and for the annual data. However, none of the associations are statistically significant at conventional levels ($p > 0.05$). The tau (Z) values of Kendall for MAM, SON and DJF were weak because they indicate the dry seasons with little or no record of rainfall. While season JJA presented moderate value (0.200, 11.307) as it represents the rainy season. Conclusively, the R^2 for the annual trend was 11.32%, indicating no trend in the series. The output of this result agrees with the findings of (Daniel, M., et al., 2014) where statistically non-significant increasing trend was recorded in all seasons (including annual time scale); while different from the results of (Asfaw et al., 2018; Negash, W., Goel, N.K., Jain, 2013) where statistically significant declining kiremt rainfall at watershed level was reported in different part of Ethiopia including the central highland.

Table 4.1: Annual and Seasonal rainfall trend analysis with Significance level (α) = 5%.

Series\Test	**Kendall's tau**	**p-value**	**Sen's slope**
MAM	**0.156**	**0.592**	**3.353**
JJA	**0.200**	**0.474**	**11.307**
SON	**0.067**	**0.858**	**3.560**
DJF	**0.248**	**0.486**	**0.000**
Ann	**0.333**	**0.210**	**18.568**

Figure 4.1. below showed the annual spatial distribution of rainfall (in millimeter) in Kano from 2011 to 2020. From the distribution, it is observed that some years received higher rainfall than some other years. The years 2011, 2019 and 2020 were seen as the wet years because more than

half of the state received above average rainfall (830mm) in the years. However, the years 2015 and 2018 were observed to be the driest years in the entire years of observations (2011- 2020). These two years records the highest rainfall of less than 1000mm even for the highest rainfall regions of the state (Doguwa Local Government).

Spatially, the distribution of rainfall for the aforementioned years were presented on the map as low, moderate and high. Generally, southern tip of the of the state mostly covering the entire Doguwa and some part of Tudun wada local governments, especially northern part of Tudun wada and its neighboring local governments such as Sumaila, Garko, Rano, Kibiya, Bebeji and part of Kiru received moderate rainfall in the state for the entire years of observation. North and north eastern part of the state received lower rainfall compared to other areas of the state. These areas include, Albasu, Gaya, Ajingi, Gabasawa, Gezawa, Minjibir, Danbatta, Bichi, part of kano metropolis and part of Takai. Other areas especially at the interior of the state fall within moderate rainfall in wet years and low rainfall in dry years. For example, areas like Garun Malam, Madobi, Rimin Gado and Bagwai fall within the moderate rainfall region in wet years (2011, 2013, 2017 and 2020), but received low rainfall during the dry years (2012, 2014, 2015 and 2018). This corresponds to (Adamu Mustapha et al., 2014; Halliru, 2013; Irohibe & Agwu, 2014; Luka Fitto Buba, Nura Isyaku Bello, Hamza Ahmad Isiyaka, Muhammad Alhaji, Tijjani abdulahi Yahaya, 2021; NAZİFİ et al., 2021; Yakubu, 2010) where the researchers indicated that Kano is characterized by rainfall variability around a long-term annual total ranging from less than 600 mm in the northernmost parts to 800 mm in the middle (around Kano City) to 1000 mm in the southern tips. Therefore, the decadal variability of precipitation in Kano shows that the precipitation pattern was actually fluctuating over time. This variability in precipitation distribution poses a great challenge to majority of smallholder farmers who solely relied on on-set and cessation of precipitation for sowing and harvesting respectively. According to (Halliru, 2013) "the observed delay of the on-set of rainfall and the early cessation has serious impact on agriculture, for instance the production of millet, early maturing varieties of sorghum and maize, rice and wheat which farmers adopted in mitigating the severe climate conditions have substantially decline in recent years".

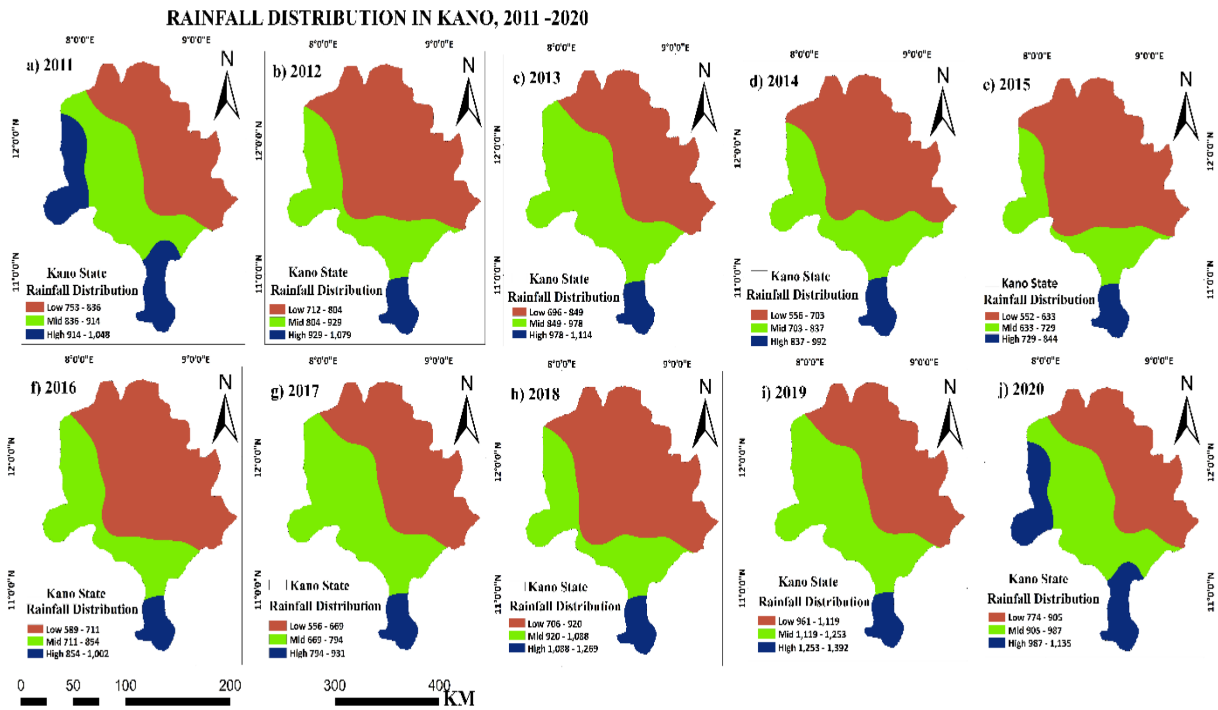


Figure 4.1. Observed Spatial **Precipitation** *Distribution in Kano from 2011 to 2020*

4.1.2: Future Precipitation Spatial Distribution

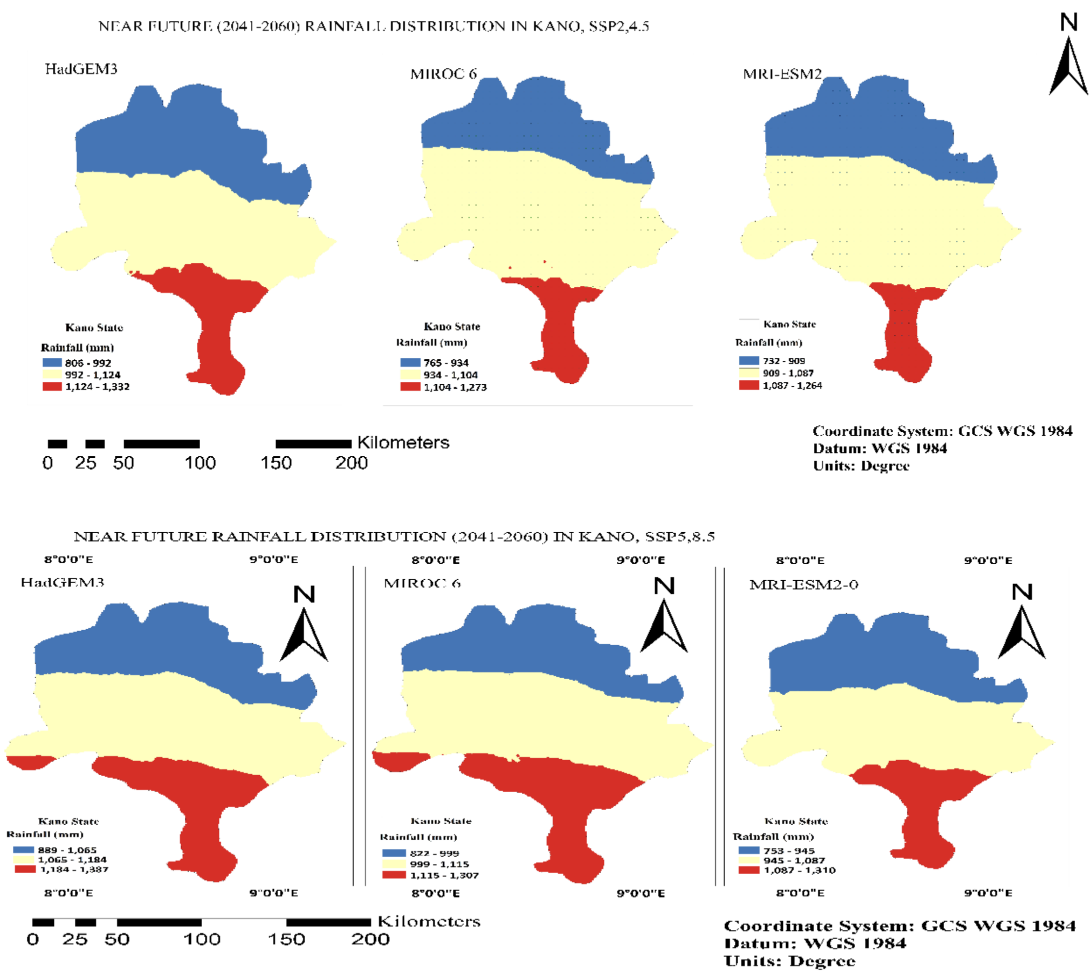
Figure 4.2 (a, b, c and d) below indicate near and far future spatial distribution of rainfall in Kano under SSP2,4.5 and SSP5,8.5 scenarios. The pattern of distribution across the three GCMs were uniform in both near and far future analysis. In terms of rainfall amount forecasted using the three different scenarios for near future (2041 -2060), HadGEM3 depicts high rainfall potentials than the remaining two scenarios with 899mm as the minimum rainfall for the entire state and 1,389mm as the maximum. But for far future (2081 – 2100), MIROC 6 emerged to be the model with high rainfall potential with minimum rainfall and maximum rainfall forecasted to be 895mm and 1,380mm respectively. Additionally, the extent of areas covered by each category of rainfall amount (low, moderate, high) varies with scenarios (near future vs. far future). The spatial extent of the three rainfall amount regions (i.e., low, moderate and high rainfall areas) was averagely identical in the near future scenarios, but for the far future, the moderate rainfall areas cover almost half of the state, covering more areas that were of high rainfall in the near future scenario. Thus, it could be deduced that, some areas that were wetter and received high rainfall at present may fall to receive moderate rainfall especially in the far future. Areas like Sumaila, Tudun Wada, part of

Kibiya, Rano and Bebeji would be affected by reduction in their annual rainfall in the far future (2081 to 2100). This pattern corresponds to observed distribution of rainfall (2011 – 2020) where southern tip of the state recorded more rainfall than the northernmost part. Therefore, the projection of rainfall in the state in the near future is close to the pattern being observed historically.

Climate change is expected to continue to increase rainfall variability, with an increase in precipitation by approximately 5-20 percent. Similarly, flooding is expected to occur alongside droughts in northern Nigeria, arising from a decline in precipitation and rise in temperature. These changes are likely to affect agricultural production in the state, which is mainly rainfed. The findings of some studies (Maina & Liman, 2020; Nneji et al., 2019; Shiru et al., 2020) on climate projection in Nigeria and Kano supports this present findings, that rainfall shows a fluctuating trend in the future which likely has the potential to affect the performance of maize grain yield under rainfed farming condition in the study area.

a)

b)



c)

d)

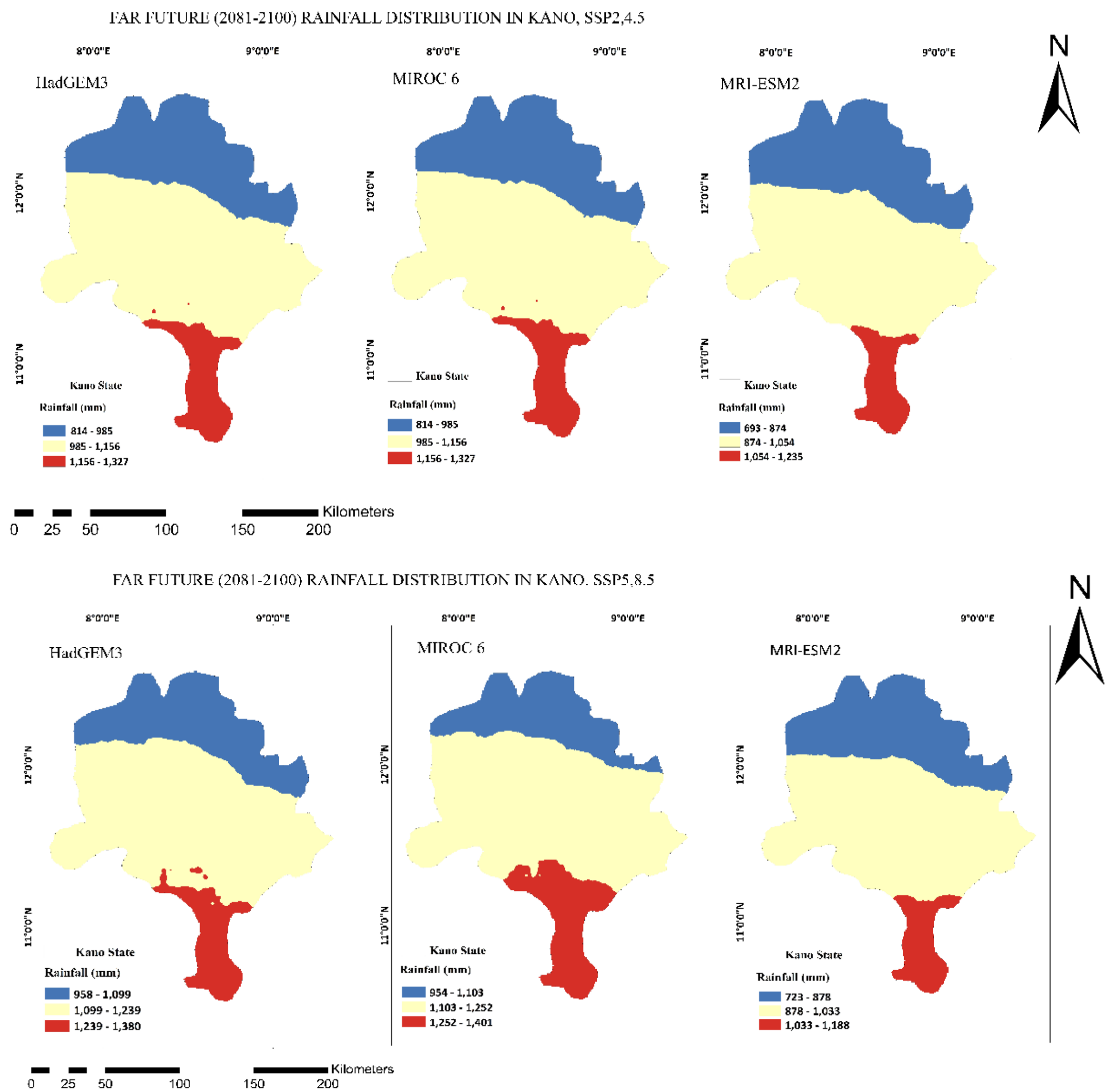


Figure 4.2 (a, b, c & d). Near and Far Future Spatial Distribution of Precipitation in Kano

4.1.3. Observed Minimum and Maximum Temperature

Table 4.2 below summarize the average minimum and maximum temperature trend over the study area from the period 2011 to 2020. For maximum temperature, the Kendall's tau coefficient is -0.422 indicating a moderate negative trend while for minimum temperature the coefficient is 0.333 indicating a moderate positive trend. Similarly, the p-value suggests that there is no statistically significant trend for both variables at a conventional significance level of 0.05. Additionally, the Sen’s slope indicates that for each unit increase in the variables being tested, maximum temperature decreases by approximately 0.527 units while minimum temperature increases by approximately 0.564 units. Conclusively, tested temperature variable showed decreasing and increasing trends over the years. The R^2 for maximum and minimum temperature showed 61.48% and 59.65% trend impact over the years. This trend has an impact on maize yield in the study area, as studies showed that slight rise in temperature has a significant impact on the yield of some cereal crops including maize.

Table 4.2 Annual Minimum and Maximum Temperature trend with Significance level (α) = 5%.

Series\Test	**Kendall's tau**	**p-value**	**Sen's slope**
Tmax Average	**-0.422**	**0.107**	**-0.527**
Tmin Average	**0.333**	**0.210**	**0.564**

Figure 4.3 (a &b) below showed the annual spatial distribution of temperature (in °C) over the years in the study area. The distribution indicates some years with higher temperatures than others. These years are 2013, 2016, 2017, 2018 and 2019 with a record range of 39.03°C to 39.43°C. The range of annual temperature falls within 32°C (lowest) to around 39°C (highest). The places that remain constantly at low temperature variation are found along the southwestern and southern tip of the state. These are areas around Doguwa, Rogo and some parts of Kiru, Karaye and Tudun Wada. The range of temperature in these areas falls around 32°C to 35°C. Similarly, moderate temperature falls within the range of 34°C to 36°C in areas covering the central parts of the state such as Garun Malam, Kabo, Rimin Gado, Gezawa, Dawakin Kudu among others. Whereas, the areas situated at the extreme northern parts of the state consisting of those regions close to the vicinity of the desert such as Gabasawa, Danbatta and Ajingi records the highest temperature of 36°C to 39°C in all the hot years.

This distribution and spatial extent remain the same for minimum temperature in all the observed years but with an annual range of 15°C to 17°C in all the years. As indicated in (Adamu Mustapha et al., 2014), temperature in the region is generally high throughout the year, with seasonal changes showing gradual increase from March through April where maximum values can reach up to 43°C. Based on temperature element, there are three main seasons which are; cool and dry recording mean monthly temperatures between 21 and 23°C. The hot and dry season as well as the wet and warm season characterised with temperature ranges between 30°C and 26°C respectively.

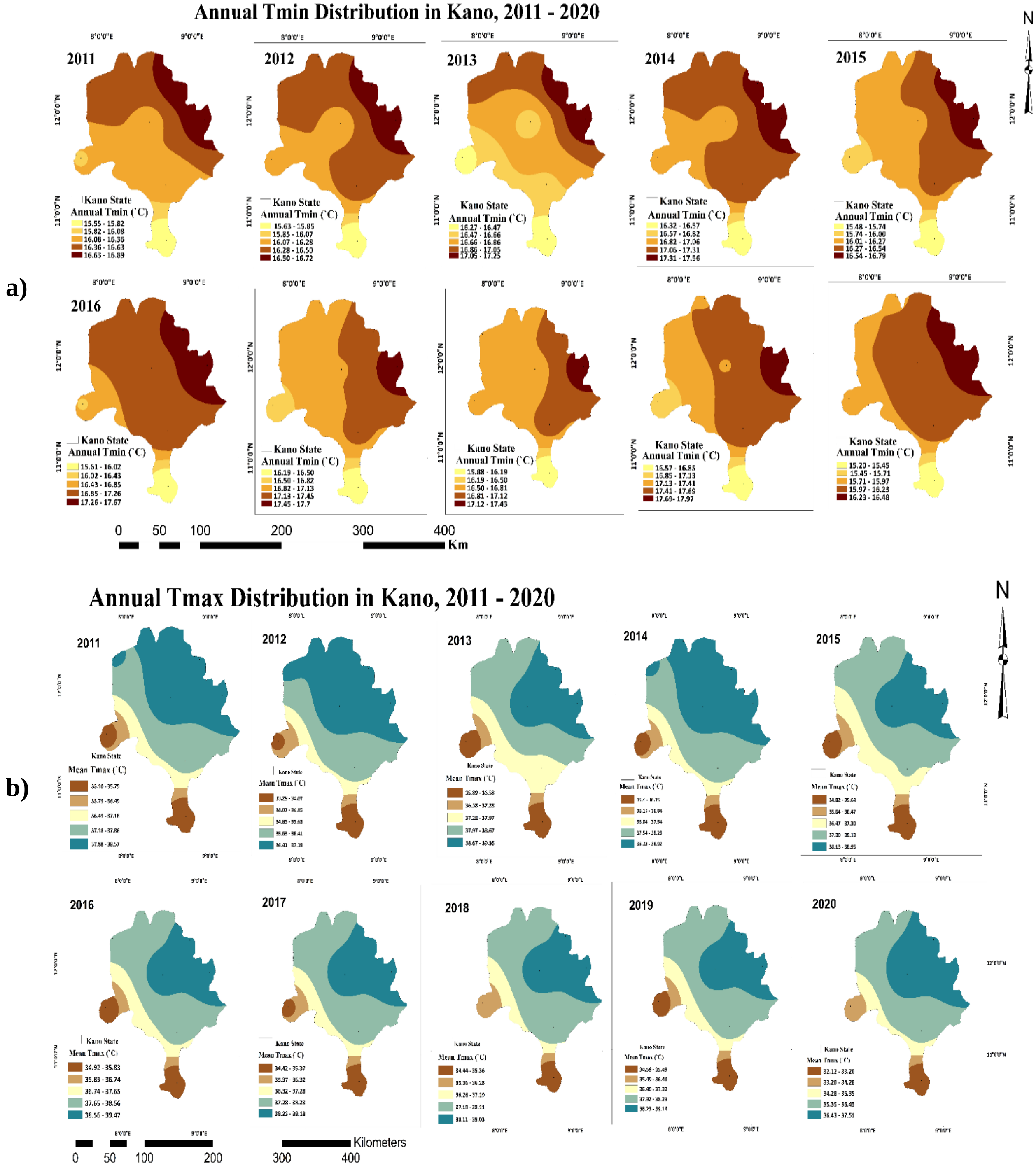
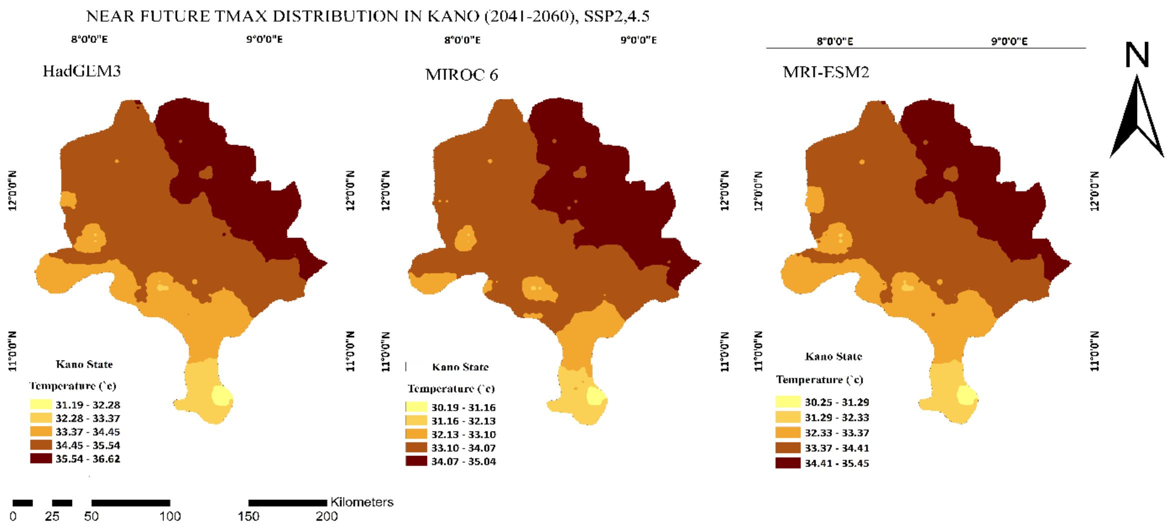


Figure 4.3.(a &b): Observed Spatial Minimum and Maximum Temperature Distribution in Kano

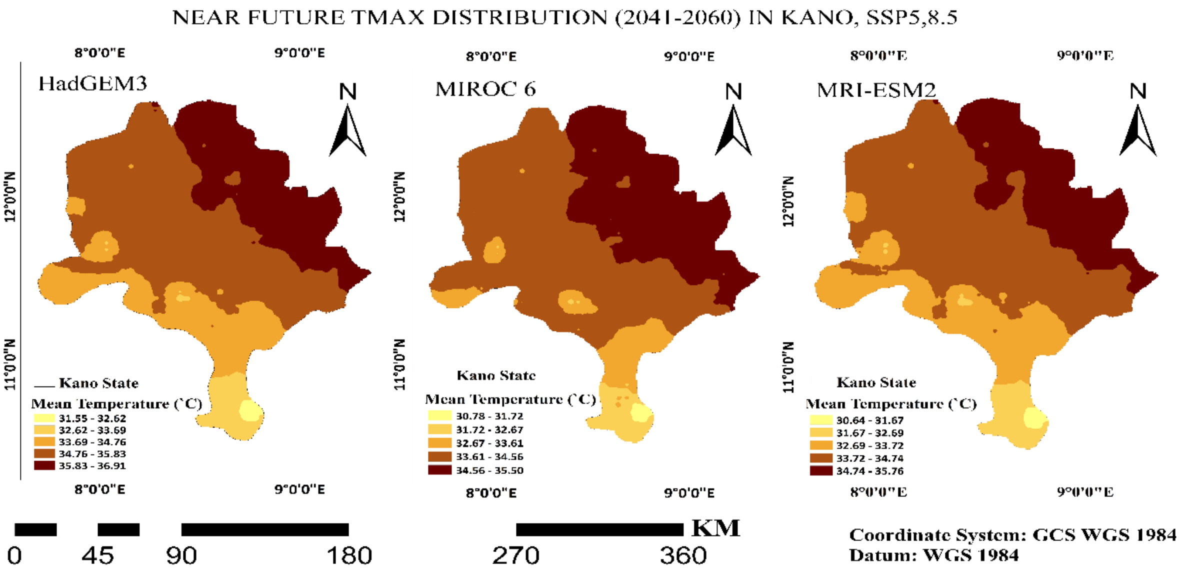
4.1.4. Future Temperature Distribution in Kano

Figure 4.2 (a, b, c and d) below indicate near and far future spatial distribution of temperature in Kano under SSP2,4.5 and SSP5,8.5 scenarios. The pattern of distribution across the three GCMs were uniform in both near and far future analysis. In terms of temperature values forecasted using the three different scenarios for near future (2041 -2060) under both SSPs, HadGEM3 depicts high temperature potentials than the remaining two scenarios with 31 as the minimum temperature for the southern tips and 36 as the maximum temperature for the northernmost parts. However, for far future (2081 – 2100), MRI-ESM2 emerged to be the model with high temperature potential with minimum and maximum temperature forecasted to be 35 to 40 respectively. Additionally, the extent of areas covered by each category of temperate regions which are classified into five varies very slightly with scenarios (near future vs. far future), with the exception of the MRI-ESM2. The spatial extent of the five temperate regions was averagely identical in the far future SSP2,4.5 scenario, but for far future MIROC 6 SSP5,8.5 model, the lowest temperature areas cover a very small portion of the southern part of the state. Thus, it could be deduced that, some areas that were cooler at present may fall under warmer regions especially in the far future. Areas like Sumaila, Tudun Wada, part of Kibiya, Rano and Bebeji would be affected by higher temperatures in the far future (2081 to 2100). However, contrasting the results of (Maina & Liman, 2020), in which the projected maximum temperature clearly shows an increasing trend over the baseline period. That is to say, almost all the years under projection exceeded all the years under baseline period. This is clearly a determinant factor of climate change impact on agricultural production. The findings of this results show a pattern that corresponds to observed distribution of temperature (2011 – 2020) where southern tip of the state recorded lower temperature than the northernmost part. Therefore, the projection of temperature in the state in the near future is closer to the baseline period.

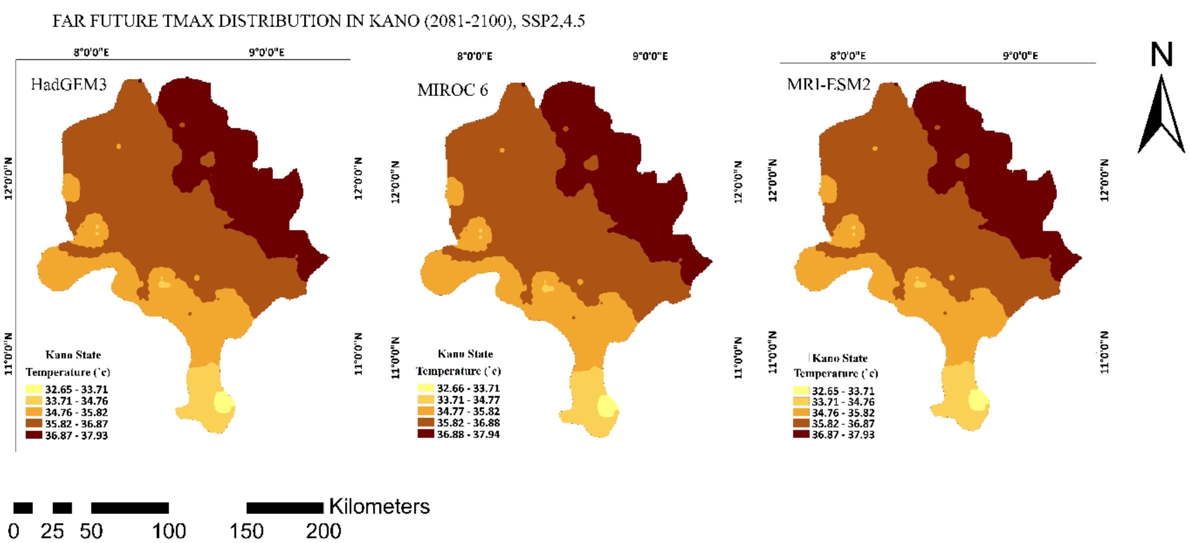
a)


NEAR FUTURE TMAX DISTRIBUTION IN KANO (2041-2060), SSP2,4.5
HadGEM3
MIROC 6
MRI-ESM2
N
Kano State
Temperature (˚c)
31.19 - 32.28
32.28 - 33.37
33.37 - 34.45
34.45 - 35.54
35.54 - 36.62
Kano State
Temperature (˚c)
30.19 - 31.16
31.16 - 32.13
32.13 - 33.10
33.10 - 34.07
34.07 - 35.04
Kano State
Temperature (˚c)
30.25 - 31.29
31.29 - 32.33
32.33 - 33.37
33.37 - 34.41
34.41 - 35.45
Kilometers
0 25 50 100 150 200

b)


NEAR FUTURE TMAX DISTRIBUTION (2041-2060) IN KANO, SSP5,8.5
HadGEM3
MIROC 6
MRI-ESM2
Kano State
Mean Temperature (˚C)
31.55 - 32.62
32.62 - 33.69
33.69 - 34.76
34.76 - 35.83
35.83 - 36.91
Kano State
Mean Temperature (˚C)
30.78 - 31.72
31.72 - 32.67
32.67 - 33.61
33.61 - 34.56
34.56 - 35.50
Kano State
Mean Temperature (˚C)
30.64 - 31.67
31.67 - 32.69
32.69 - 33.72
33.72 - 34.74
34.74 - 35.76
KM
0 45 90 180 270 360
Coordinate System: GCS WGS 1984
Datum: WGS 1984

c)


FAR FUTURE TMAX DISTRIBUTION IN KANO (2081-2100), SSP2,4.5
HadGEM3
MIROC 6
MRI-ESM2
N
Kano State
Temperature (˚c)
32.65 - 33.71
33.71 - 34.76
34.76 - 35.82
35.82 - 36.87
36.87 - 37.93
Kano State
Temperature (˚c)
32.66 - 33.71
33.71 - 34.77
34.77 - 35.82
35.82 - 36.88
36.88 - 37.94
Kano State
Temperature (˚c)
32.65 - 33.71
33.71 - 34.76
34.76 - 35.82
35.82 - 36.87
36.87 - 37.93
Kilometers
0 25 50 100 150 200

d)

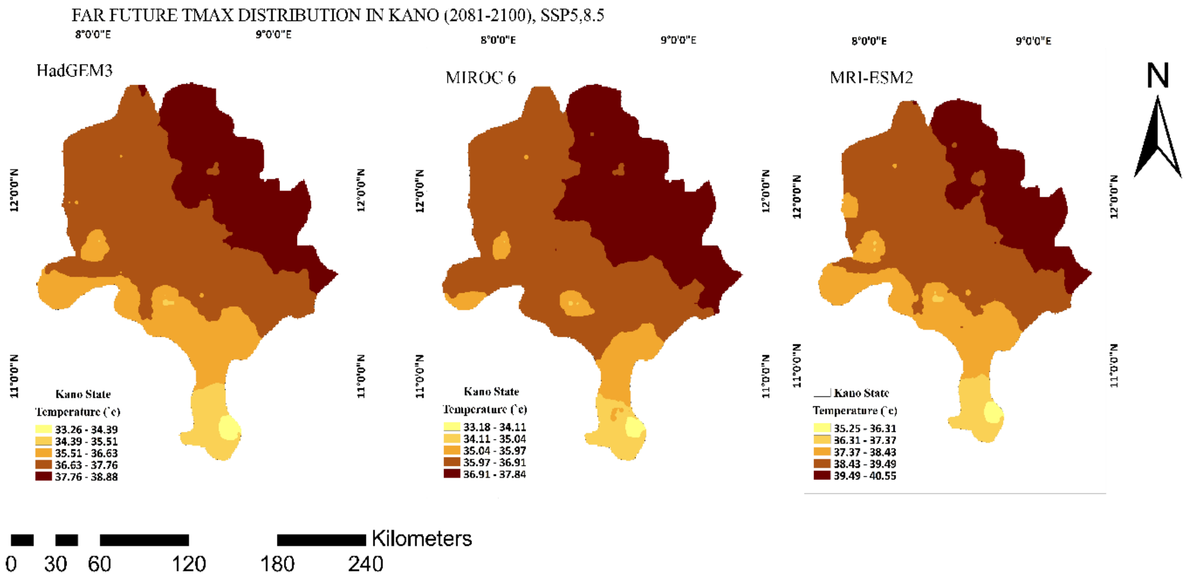


Figure 4.4 (a, b, c and d) Near and Far Future Temperature Distribution in Kano

4.2. Temporal Analysis of Historical Temperature and Precipitation in Kano

The temporal variation of seasonal and annual precipitation over Kano State is presented in Fig. 4.4a. DJF being the harmattan season shows no record of precipitation. The MAM season, which presents the summer season and onset of rainy season recorded very slight rainfall over the years, with the highest record in 2012 at 120.5mm. Similarly, SON which is the short rain season was just slightly higher than the MAM season, with a range of low to high precipitation variability between 100mm to 215mm in 2016 and 2020 respectively. The mean annual precipitation is around 800 mm with great temporal variation occurring in the amount of precipitation received. No two consecutive years record the same amount, except with slight variations in either increase or decreasing amount. The annual amount of precipitation may reach about 1000 mm in the southern Kano (part of Doguwa and Tudun-Wada local governments). While in the northern extreme, the annual value received is lower than 800 mm especially toward the vicinity of desert. These inconsistency in precipitation variability resulted in frequent extreme weather events such as the 2012 and 2020 floods as well as 2015 drought cases in the state(acaps. Priorities, 2022; Haider, 2019).

a)

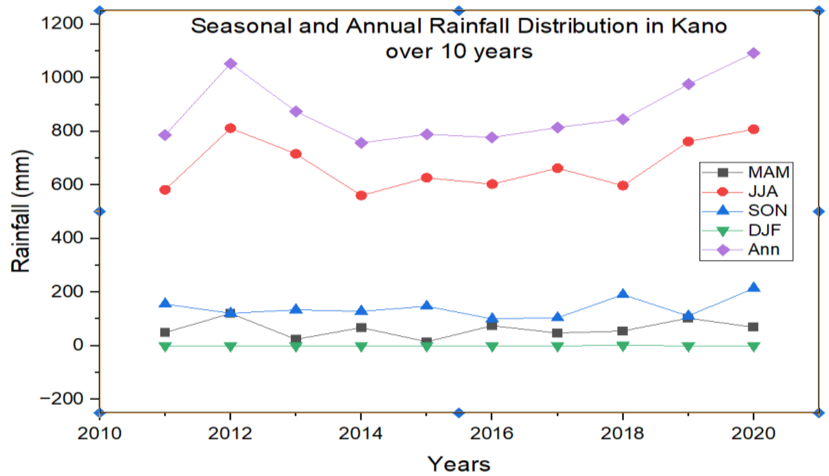


Figure 4.4a: Temporal Variation of Seasonal and Annual rainfall in Kano

In figure 4.4b and c, mean annual minimum and maximum temperatures were presented, with records taken from eight different synoptic stations spread over the spatial extent of the states. The synoptic stations are; Tsanyawa, Kunchi, Gabasawa, Ajingi, Gwarzo, Rogo, Tudun Wada and Doguwa located on latitudes 12.2743, 12.5399, 12.2555, 12.2555, 11.9064, 11.8795, 11.2578, 10.7121 and longitudes 7.8697, 8.2872, 8.875, 9.1414, 8.5262, 7.7719, 8.7085, 8.7132 respectively. Tsanyawa, KUnchi, Gabasawa and Ajingi being situated inward towards the vicinity of the desert shows a record of higher temperatures than the areas located at the southern tips around Doguwa, Rogo and Tudun Wada. From the graph, 2016 and 2019 witnessed higher minimum and maximum temperature values. According to (Yakubu, 2010), Kano city is typically very hot throughout the year, though December through February are noticeably cooler, especially at night with average low temperatures ranging from 11°C to 14°C.

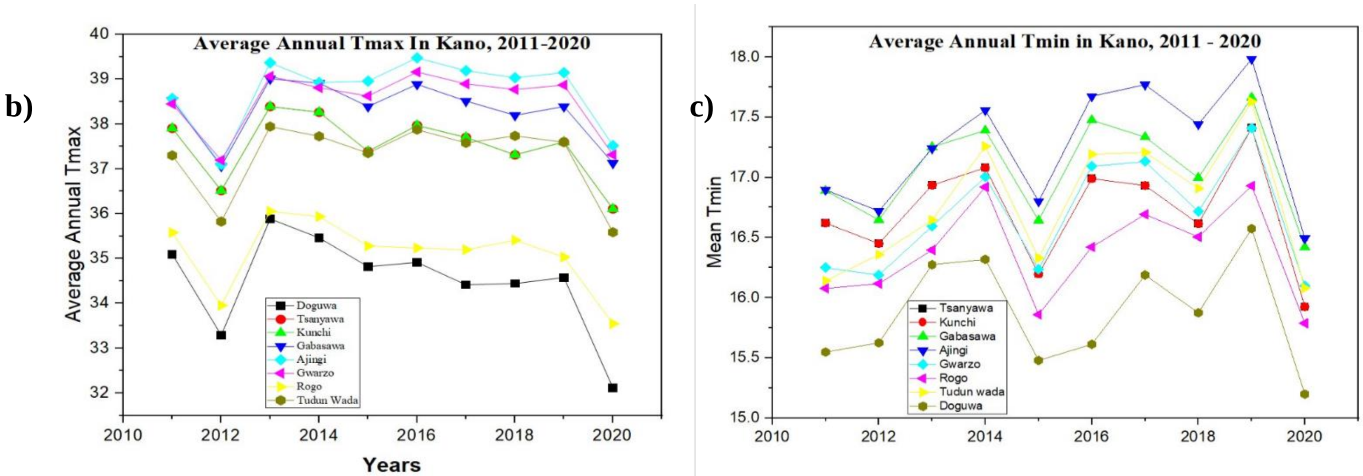


Figure 4.4 Temporal Variation of (b) Minimum Temperature (c) Maximum Temperature in Kano

4.3. Regression Analysis of Dependent and Independent Variables

This section presented the results of regression of maize yield as the dependent variable, and precipitation and temperature as independent variables. To give an overview of the central tendency and variability within the variables of interest, table 4.3 below summarize the statistics. Remarkably, the high standard deviation in rainfall suggests a wide range of rainfall conditions in the dataset.

Table 4.3. Descriptive Statistics of the Tested Variables

	Mean	Std. Deviation	N
Maize Yields	2146.4000	831.30636	10
Max. Temperature	36.3150	2.48054	10
Rainfall	178.4700	307.80646	10

The correlation analysis in table 4.4b below shows that there is a moderate positive correlation between maize yield and maximum temperature, and a moderate negative correlation between maize yield and rainfall. However, neither correlation is statistically significant at the $p < 0.05$ level, suggesting caution in interpreting the relationships**.** Similarly, the model summary in table 4.4a, the R^2 value indicates that approximately 25.1% of the variance in maize yield is explained by the model. However, the adjusted R^2 is much lower at 0.037, suggesting that when the number of predictors and sample size are accounted for, the explanatory power of the model diminishes significantly. Additionally, this indicates that after accounting for the number of predictors, the model does not explain much of the variance in maize yield beyond what would be expected by chance. It suggests that other variables not included in the model might better explain the variance in maize yield or that the relationship between the predictors and the outcome is more complex than can be captured by a linear model. Furthermore, the Durbin-Watson statistic was 1.383, which is usually used to detect the presence of autocorrelation in the residuals from a regression analysis. Values of this statistic range from 0 to 4, with values around 2 indicating no autocorrelation. A value of 1.383 suggests a positive autocorrelation, although it's not severe. This could imply that the data might have a time series component or that there are missing variables that influence the trend of maize yield over time.

Table 4.4a: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.501[a]	.251	.037	815.66403	.251	1.174	2	7	.363	1.383

a. Predictors: (Constant), Rainfall, Max. Temperature

b. Dependent Variable: Maize Yield

Table 4.4b: Correlation between Maize Yield, Temperature and Rainfall

		Maize Yield	Temperature	Rainfall
Pearson Correlation	Maize Yields	1.000	.406	-.406
	Max. Temperature	.406	1.000	-.314
	Rainfall	-.406	-.314	1.000
Sig. (1-tailed)	Maize Yields	.	.122	.122
	Max. Temperature	.122	.	.189
	Rainfall	.122	.189	.
N	Maize Yields	10	10	10
	Max. Temperature	10	10	10
	Rainfall	10	10	10

The ANOVA results in table 4.5a below show that the regression model is not statistically significant, implying that the model does not significantly predict maize yield based on the variables included. While in table 4.5b, VIF (Variance Inflation Factor) for both Max. Temperature and Rainfall is approximately 1.109, indicating no collinearity issue as VIF values are well below the threshold of 5 or 10.

Table 4.5a: ANOVA[a] **F (2, 7) = 1.174, p = 0.363.**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1562477.762	2	781238.881	1.174	.363[b]
	Residual	4657154.638	7	665307.805		
	Total	6219632.400	9			

a. Dependent Variable: Maize Yield

b. Predictors: (Constant), Rainfall, Max. Temperature

Table 4.5b: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-1469.292	4254.814		-.345	.740	-11530.328	8591.745					
	Max. Temperature	103.667	115.434	.309	.898	.399	-169.291	376.625	.406	.321	.294	.902	1.109
	Rainfall	-.835	.930	-.309	-.897	.399	-3.035	1.365	-.406	-.321	-.294	.902	1.109

a. Dependent Variable: Maize Yield

The analysis conducted suggests that, within the scope of the data and the model used, maximum temperature and rainfall do not significantly predict maize yield. The model explains a small portion of the variance in maize yield, and its predictors are not statistically significant. Furthermore, the adjusted R^2 value and the ANOVA results underscore the model's limited explanatory power and significance in predicting maize yield based on the variables examined. Both maximum temperature and rainfall had high p-values (0.399 for both), indicating that they are not statistically significant predictors of maize yield in this dataset. This suggests that any observed changes in maize yield cannot confidently be attributed to changes in these variables within the sample studied. The wide confidence intervals for the coefficients of both maximum temperature (-169.291 to 376.625) and rainfall (-3.035 to 1.365) indicate a high degree of uncertainty about these estimates. The fact that the confidence interval for rainfall includes both negative and positive values further complicate the interpretation, suggesting that the effect of rainfall on maize yield is not clearly defined or is possibly moderated by other factors not included in the model. The analysis could be deepened by considering external factors or interactions between variables that were not included in the original model. For instance: there could be significant interaction effects between maximum temperature and rainfall that were not accounted for. For example, the impact of temperature on maize yield might depend on whether conditions are wet or dry. The relationships between maize yield and both maximum temperature and rainfall might be non-linear, which would not be captured by a linear regression model. For example, there might be a threshold effect where temperature or rainfall beyond certain points has a diminishing or adverse effect on maize yield. Other factors such as soil fertility, maize varieties, farming practices, or additional climatic factors (e.g., humidity, solar radiation) could play significant roles in determining maize yield and could provide a more comprehensive understanding when included in the analysis. Similarly, while there are observed relationships between maize yield and both maximum temperature and rainfall, these relationships are not statistically significant in this dataset. This finding suggests that further research, perhaps with a larger dataset or additional explanatory variables, is necessary to better understand the factors influencing maize yield. Conclusively, while the initial analysis suggested that maximum temperature and rainfall do not significantly predict maize yield in the dataset analyzed. However, this deeper examination highlights the limitations of the current model and suggests areas for further research. Additional data collection, consideration of more complex models (including non-linear relationships and interaction effects), and inclusion of more variables could enhance understanding and predictive power regarding the factors influencing maize yield.

A study conducted in Ethiopia indicated that rainfall and temperature had a combined influence of 46.72% on maize yield and thus not statistically efficient in predicting maize yield, implying that other factors besides rainfall and temperatures may be used to explain the variation in maize. Similarly, in (Luka Fitto, et al., 2021), various independent variables are considered in running the model, and the findings indicated that evapotranspiration contributes more on maize seasonal yields fluctuations, followed by temperature, atmospheric humidity and rainfall with least impacts respectively. This corresponds to the limitations that may have hindered the successful predictability of the dependent variable by the independent variables.

4.4. Crop Simulation and Validation

Results for simulation of maize yield using DSSAT software and an experimental farm trial, weather and soil data prove unsuccessful as the model reported 0 kg/ha yield from the simulation analysis. Similarly, all measured results are not fully captured in the model. Similar analysis needs to be carried out with more experimental data to run the simulation and validate the analysis obtained in order to properly forecast future maize yield under different climate scenarios. However, results from previous researches indicated that maize production could likely decline due to climate change in Nigeria. We therefore intend to use the DSSAT-CEREZ-Maize model to assess the response of maize to climate variability and trends in Kano State, Nigeria. The CERES-Maize model of DSSAT has been evaluated and used by many researchers who found good correlations between observed and simulated values for a wide range of experimental and fertilization practices against field data and environmental conditions. Unfortunately, due to paucity of time and technical errors from the model in use, the present study could not produce a viable result.

CHAPTER FIVE

5.0. SUMMARY, RECOMMENDATIONS AND CONCLUSION

5.1. Summary

Assessing the impacts of climate variability on maize yield through spatiotemporal and regression analysis as well as validation, calibration and forecasting maize yield using crop simulation model is significant for increased food security in the study area. Spatially and temporally, precipitation and temperature indicate a uniform pattern and trends over the observed years, while the future projection indicates substantial increase in amount and rate of precipitation and temperature in the far future, suggesting that, these two climatic variables can pose greater challenge positively or negatively on maize yield for rainfed dependent regions. Even though, the relationship between the dependent variable(maize) and the independent variables (temperature and precipitation) shows that there are observed relationships between maize yield and both maximum temperature and rainfall, these relationships are not statistically significant to predict maize yield, unless other variables are taken into account.

5.2. Recommendations

It is recommended that other field trials on crop be conducted in order to obtain primary data to be used for crop modelling and simulation in the study area. Similarly, other variables such as soil moisture, crop varieties, irrigation and cropping time considering climate-smart practices be considered by farmers for effective increase in maize yield in the study area. Additionally, it is recommended that, for a better outcome of yield forecast, ample time should be given to conduct on-farm experiment coupled with weather and soil analysis needed to be input in the DSSAT-CEREZ-Maize model.

5.3. Conclusion

Based on the results obtained from this study, it can be concluded that, while the initial analysis suggested that maximum temperature and rainfall do not significantly predict maize yield in the dataset analyzed. However, this deeper examination highlights the limitations of the current model and suggests areas for further research. Additional data collection, consideration of more complex models (including non-linear relationships and interaction effects), and inclusion of more variables could enhance understanding and predictive power regarding the factors influencing maize yield. Furthermore, an experiment on maize together with soil analysis and weather record should be conducted for use in the crop simulation model in order to predict future maize yield and make informed decisions about ways of improving the yield of maize under different climatic and non-climatic conditions for increased food security in the study area. Further research that will incorporate all the limitations encountered in the present research is therefore needed.

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