Assessment of Selected Agroclimatic Indices on Maize Yield Forecasting Under Climate Change in Nigeria

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Abstract. This study investigates the relationship between climate, agroclimatic indices, and maize yield in Nigeria, focusing on diverse agroecological zones. Climate change is poised to significantly impact agricultural output. Analysis of historical data reveals varying sensitivities to weather changes in Nigeria's agroecological regions. Regional climate impact assessments typically use annual statistical models, which may not capture sub-seasonal weather variations and often assume a constant relationship between crops and weather. Crop yield anomalies were created to remove non-weather-related influences from a time series dataset. Also, agroclimatic indices were incorporated into forecasting models as inputs to offer more relevant information for estimating crop output. The research demonstrates the critical role of climate factors such as rainfall in March and minimum temperatures in shaping maize yield in Nigeria. By expanding the scope to include a broader range of climate-related elements, this study has illustrated how incorporating agroclimatic indices into crop yield forecasting models can enhance forecast accuracy and reliability. The study reveals that different agroecological zones may face varied outcomes with regions in the south recording more negative maize yield anomalies as oppose to the north. The research underscores the complexity of the relationship between climate, agroclimatic indices, and crop yield in Nigeria. It provides essential insights for policymakers, farmers, and researchers to make informed decisions and develop strategies for ensuring food security and agricultural sustainability in the midst of a changing climate in Nigeria.

Keywords: Climate Change, Maize, Nigeria, Agroecological zones

1. Introduction

The yield of crops in agriculture is influenced by several factors such as soil properties, agronomic practices, water availability etc., however, weather poses as the single most important and uncontrollable factor influencing crop yield [1]. Crop's performance and yield are sensitive to trend in climate, with responses to long–term trends in average rainfall and temperature differing among crop species throughout their life cycle [2]. Some crops are more tolerant than others to certain types of stresses, and at each phonological stage, different types of stresses affect each crop species in different ways. For example, the increase in average temperature during the growing season causes plants to use more energy for respiration for their maintenance and less to support their growth. [3] reported that with a 1°C increase in average temperatures, yields of the major food and cash crop species will decrease between 5 to 10 percent. Similarly, [2] reported that at higher average temperature plants are precipitated to complete their growing cycle more rapidly, lowering yields.

The relationship between specific weather parameters and crop yield varies depending on the crop type, location, and growth stage amongst other factors. Hence, an understanding of the relationship between weather information and how it affects crop yield is imperative to safe guarding agricultural productivity especially with the encroaching impacts of climate change. The impact of rainfall on crop yield for example depends on the timing, intensity, and duration of rainfall events. [4] reports that insufficient rainfall or drought stress, leads to reduced plant growth and yields. [5] estimates up to 37% reduction in maize yield as a result of drought in the United States as well as a 34% reduction due to excess rainfall. Similarly, optimal temperature is a crucial factor influencing crop growth and development, with [6] reporting that temperature-related extremes may better explain differences in some crop yield. Also, the relationship between ideal temperature range, and yield may be more complex, as other factors like such as soil moisture, humidity, wind and sunlight also come into play.

The challenge in Africa's food availability is complex as the crop yield per hectare is on an increase, but slower in comparison to the rate of population growth [7]. Also, the potential effects of climate change on crop performance for the continent have been projected to be both positive and negative, depending on the specific climate model, scenario, and crop modelling methodology used. Food security remains a high-priority development target for the region which many already deemed food insecure and concerted efforts towards food security may become easily derailed by the realities of climate change. Climate change is expected to have a broadly negative impact on crop yields, some studies suggest that certain areas may experience longer growing seasons and warmer temperatures due to climate change [8], [9]. [10] reports between a 20 to 45% decrease for maize yields, 5 to 50% for wheat and 20 to 30% for rice yields. While some studies suggest that certain areas may experience longer growing seasons, and increased yield potentials.

Among the countries in Africa, Nigeria is ranked the second largest producer of maize. Data released by the United States Department of Agriculture (USDA) reveals that maize production in the country has been steadily rising and reached its highest level in 2021 since gaining independence [11]. However, despite the substantial production volumes, Nigeria's maize yield per hectare remains relatively low, at less than 2 metric tonnes per hectare. This places the country among the lowest maize-yielding nations in Africa, trailing behind countries like Egypt and South Africa, where maize yields reach 7.7 metric tonnes per hectare and 5.3 metric tonnes per hectare, respectively. In the past, the majority of maize grain production in Nigeria was concentrated in the southwestern region.

Nigeria's agricultural system, similar to most countries in sub-Saharan Africa is highly vulnerable to change in climate as the farming system is comprised mainly of rainfed and non-homogenous small holder farming [12], [13]. Evidences show that CC has already impacted maize yield and will continue to have a significant impact on agricultural planning, practice, technology and output for the country [14]. According to [15], it was predicted that the rise in temperature, under current CO_2 levels, would have a more significant impact on maize productivity in the humid-forest and semi-arid agroecological zones. This effect is projected to result in reductions of approximately 18% and 13% in the respective zones. Also, the rising temperatures and altered rainfall patterns have led to changes in the length and timing of growing seasons, affecting the optimal timing for planting and harvesting crops in Nigeria. CC has been reported to have led to the spread of late onset and early cessation of precipitation phenomenon from only a few areas between the years of 1941 – 1970 to the most part of the country between the years of 1971-2000 [16]. However, it is important to recognize that the impact of climate change on crop yields and the adaptation strategies vary depending on the specific characteristics of local and regional resources. Therefore, the methodology employed in this study aligns with the FAO's notion that a complex landscape can be characterized as a series of uniform production areas, referred to here as agroecological zones [17].

Additionally, climate impact assessments conducted at the regional level often rely on annual statistical modelling approaches [3], [18]. However, these models may not fully capture sub-seasonal weather fluctuations and typically assume a constant relationship between crops and weather. To provide the forecasting model with data more directly relevant to crop yield, we incorporated various agroclimatic indices into our analysis. In this study, we examined a total of 98 distinct agroclimatic indices. Within this context, the study had two primary objectives: (i) to evaluate the effects of climate change on maize yields in Nigeria and (ii) to assess the potentials if agroclimatic indices in improving maize yield forecasting. This was achieved by identifying the most significant agroclimatic indices for predicting crop yields, quantifying sensitivities of maize production of agroecological zones to weather variations.

2. Materials and Methods

The research from the methods of [1], [19] follows a three-phase approach: Data Input and Preprocessing, Evaluation of Agroclimatic Indicators and Time-Series Analysis, and Crop Yield Modelling and Forecast (Figure1.). The methodology is structured to address two main questions. First, it investigates the significance of extreme weather indices in agricultural yield forecasting and examines whether climate change will lead to positive or negative maize yield potentials in various regions.

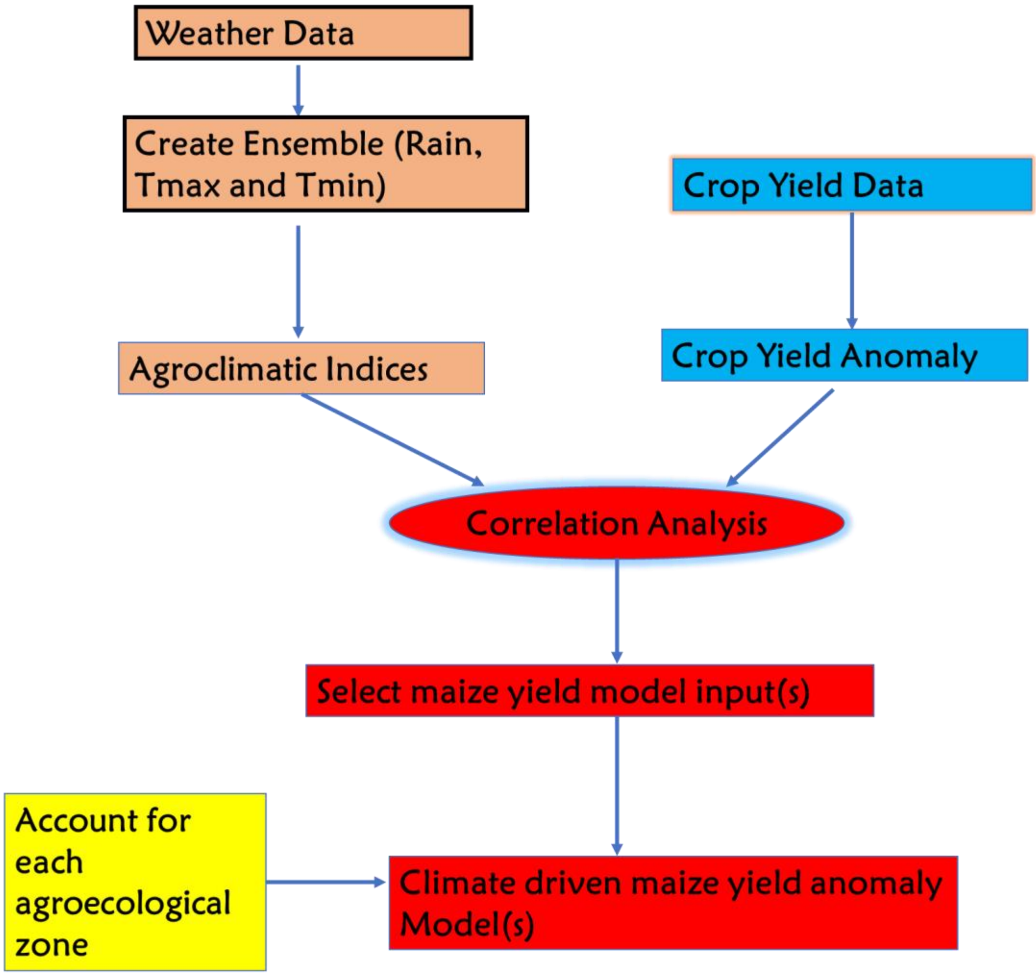


Figure 1. Development of Climate-driven Maize yield Forecasting Models

2.1 Study Area

This study was conducted over Nigeria, which has a total land mass area of 925, 796 km2 and located between latitudes 4 – 14˚N and longitudes 2 – 15˚E in West Africa. Agriculture is the backbone of Nigeria's economy, contributing over 45% of the GDP and employing more than half of the workforce [20]. Nigeria has a tropical climate with two distinct seasons: a rainy season and a dry season. The southern region receives abundant rainfall, typically spanning from March to October, with coastal areas like the Niger Delta receiving over 4,000mm of annual rainfall. The southern rainy season has a peak in June and is briefly interrupted by the August break, followed by another shorter rainy season from September to mid-October. The dry season lasts from late October to early March, with higher temperatures in the north from March to June and in the south from February to April, with daytime temperatures exceeding 30°C [21].

The study area is divided into seven broad agroecological zones patterned after [9] (Figure.2). Seven cities, one from each of Nigeria's agroecological zones, were selected for our analysis. These cities were chosen due to their strategic significance in their respective zones for agricultural practices, particularly cropping, and the availability of relevant references in the existing literature [22]–[24]. The seven cities included in this study are: Maiduguri representing the Sahel (11.50°N, 13.9°E), Birnin-Kebbi representing the Sudan (12.28°N, 04.13°E), Kaduna representing the Northern Guinea Savannah (10.3°N, 7.2°E), Bida representing the Southern Guinea Savannah (09.06°N, 06.01°E), Ilorin representing the Derived Guinea Savannah (10.5°N, 04.10°E), Jos representing the Mid-altitude (09.52°N, 08.45°E) and Ondo representing the Humid Forest (07.06°N, 04.50°E) agroecological zones.

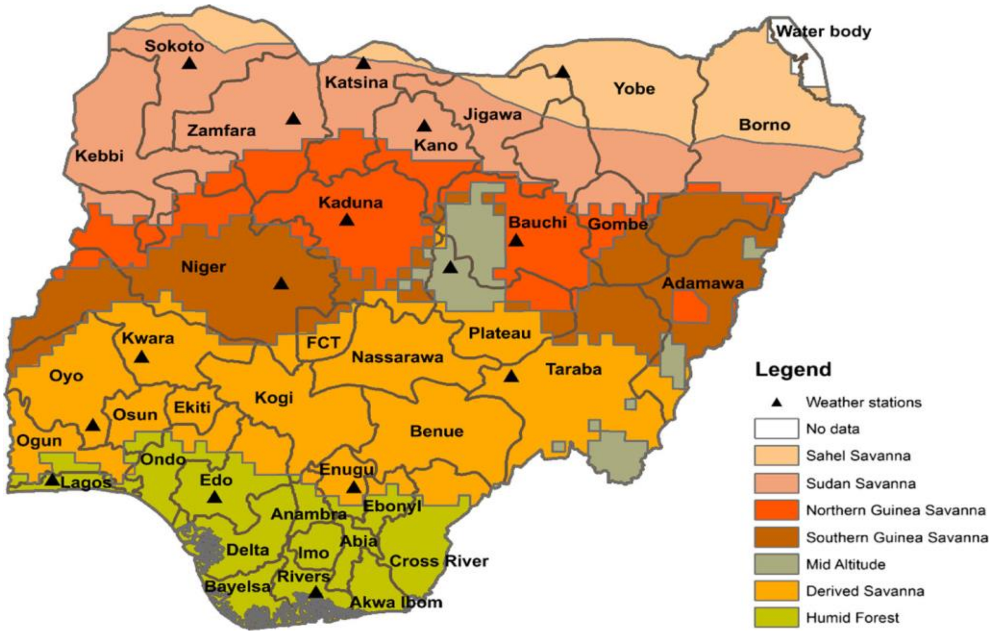


Figure 2: Agroecological Zones of Nigeria (Adapted from [9])

2.2 Meteorological Data

This study utilizes two distinct sets of meteorological data: an observation dataset and a simulation dataset. The historical data is obtained from the high-resolution (0.5x0.5 degree) gridded time-series (TS) data of the Climatic Research Unit's (CRU) version 4.05 (CRU TS v4.05), covering the period from 1901 to 2020. Monthly rainfall and temperature data from this CRU dataset were extracted using Google Earth Pro software [25]. Additionally, for future data, we used a simulation dataset derived from seven CMIP5 Global Climate Models (GCMs) that were dynamically downscaled by the Swedish Meteorological and Hydrological Institute's Rossby Centre regional atmospheric model (RCA4). These simulation data covered the historical period from 1951 to 2005 and extended into the future, from 2006 to 2100, considering two representative concentration pathways (RCPs) scenarios: RCP 4.5 and RCP 8.5. The spatial resolution of the SMHI-RCA4 regional climate model output is approximately

0.44° (about 50 km). For more details on the GCMs used in this study, including their names, resolution, and characteristics, please refer to Table 1. The SMHI-RCA4 regional climate model's reliability and ability to simulate seasonal and annual climate patterns have been extensively described and assessed in various studies [26]–[29]. These studies generally found that the model performed satisfactorily in replicating these climate patterns, with only a few exceptions.

Table 1: List of GCM model simulations downscaled by RCA4 used in this study

S/N	Modeling Center or Institute	Resolution of GCM	GCM Output Name
1	Canadian Centre for Climate Modelling and Analysis (CCCMA)	2.8° x 2.8°	CCCCMA-CanESM2
2	Centre National de Recherches Météorologiques (CNRM)	1.4° x 1.4°	CNRM-CERFACS-CNRM-CM5
3	NOAA Geophysical Fluid Dynamics Laboratory (NOAA-GDFL)	2.5° x 2.0°	NOAA-GDFL-GDFL-ESM2M
4	EC-EARTH consortium (ICHEC-EC)	1.9° x 1.3°	ICHEC-EC-EARTH
5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4° x 1.4°	MIROC-MIROC5
6	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	1.9° x 1.9°	MPI-M-MPI-ESM-LR
7	Norwegian Climate Centre	2.5° x 1.9°	NCC-NorESM1-M

2.2.1 Multiple Model Ensemble of Monthly Precipitation and Temperature

Many impact studies have traditionally relied on single or sets of General Circulation Models (GCMs), but there is a recent trend toward using ensembles of multiple GCMs to enhance model accuracy. In this study, the outputs of the RCM models were employed to develop ensembles using an Artificial Neural Network (ANN). The RCM's simulated climatic variables were initially compared to observations in determination across the country using the Pearson correlation coefficient. Subsequently, an ANN model was developed with highly correlated RCMs as independent variables, and the ensemble climate data generated by the ANN model was compared to observational data for accuracy assessment. The ANN procedure employed in this study was a feedforward network with input, hidden, and output layers, implementing supervised learning and backpropagation algorithms.

2.3 Maize yield and maize yield anomaly

The annual maize yield dataset at the state level, spanning from 1995 to 2015, was procured from the National Agricultural Extension and Research Liaison Services (NAERLS) for subsequent analysis. Maize yield is expressed in metric tonnes per hectare. The initial phase of the weather impact analysis involved detrending, a statistical procedure employed to eliminate non-weather-related influences. Detrending serves to extract the long-term trend or seasonality from a time series dataset, thereby facilitating the examination of inherent patterns and fluctuations [30]. The result of the detrending process is referred to as the maize yield anomaly. To correlate the maize yield anomaly with agroclimatic indices, equations 1 and 2 were utilized to calculate the anomaly in maize yield. Subsequently, the Maize Yield Anomaly Index (MYAI) was computed from the maize yield data. MYAI enables the assessment of the frequency and intensity of low and high yield years. This equation was adapted from the Rainfall Anomaly Index (RAI), initially developed by Rooy in 1965 and later employed by [31].

$$AYAI = 3\left[\frac{N - \bar{N}}{\bar{M} - \bar{N}}\right], for\ positive\ anomalies \qquad 1$$

$$AYAI = -3\left[\frac{N - \bar{N}}{\bar{X} - \bar{N}}\right], for\ negative\ anomalies \qquad 2$$

2.4 Agroclimatic Indices

Agroclimatic Indices, which represent agriculturally relevant climate parameters, act as indicators of the climate factors influencing agriculture. Many studies have demonstrated the significance of meteorological data in explaining agricultural productivity. selected agroclimatic indices, have been integrated as inputs in forecasting models to provide more directly pertinent information for crop output estimation. These indices are derived from raw weather data, aiming to enhance the understanding of the interplay between weather conditions and crop growth, ultimately assisting in agricultural decision-making. Considering the diverse range of crops and regions, a single index or indicator cannot comprehensively capture this relationship. Consequently, this study outlines a framework for selecting the most suitable agroclimatic indices in maize production for Nigeria. In the initial phase of selection, the indices were chosen based on their ease of application, ensuring that readily available codes or programs can be used to compute them, and they do not necessitate daily data inputs. Furthermore, the inputs for these agroclimatic indices were limited to maximum temperature, minimum temperature, and precipitation.

2.5 Simple and Multiple Linear Regression Models

This paper employs several regression models, including both simple linear regression and multiple linear regression techniques. Multiple linear regression, also known as multiple regression, is a statistical approach that leverages multiple explanatory variables to predict the outcome of a response variable. The process incorporates forward selection and stepwise regression methods. Specifically, stepwise multiple regression, a combination of forward selection and backward elimination, was chosen for its efficacy. The multiple linear regression is mathematically expressed in Equation 2.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + . . . + \beta_k x_k \quad (2)$$

Where:

y is the dependent variable,

x_i (i = 1, . . ., k) is the independent variable,

β_0 is the intercept of y, and

β_1 (i = 1, . . ., k) is the regression coefficient,

To determine the inputs for the regression models, we utilized five different configurations. "Input configuration (W)" focuses on direct annual weather indicators, such as annual minimum temperature (w1), maximum temperature (w2), mean temperature (w3), and precipitation (w4), along with the combination of these direct weather indicators (wn). Conversely, "Input configuration (I)" involves agroclimatic indices in addition to the direct weather indicators. The selection of inputs for this second model was carried out using the stepwise regression method, which involves multiple rounds of regression, iteratively eliminating the variables with the weakest correlation. The final selection is based on specific Stepwise-Regression Criteria, including a probability threshold for inclusion and removal (probability of F to enter <= 0.050, Probability of F to-remove >= 0.100. Variables are added to the model if their p-value is less than or equal to 0.05 and are removed from the model if their p-value is greater than or equal to 0.1).

From the regression output, we can derive valuable insights from various statistical measures, including Pearson coefficient, multiple coefficients of determination (R^2), and multiple correlation coefficient (R). The development of these models relied on data from the years 1995-2010, while the subsequent testing phase used data from 2011-2019.

3. Results and Discussions

3.1 Summary of Metrological and Maize Yield Datasets

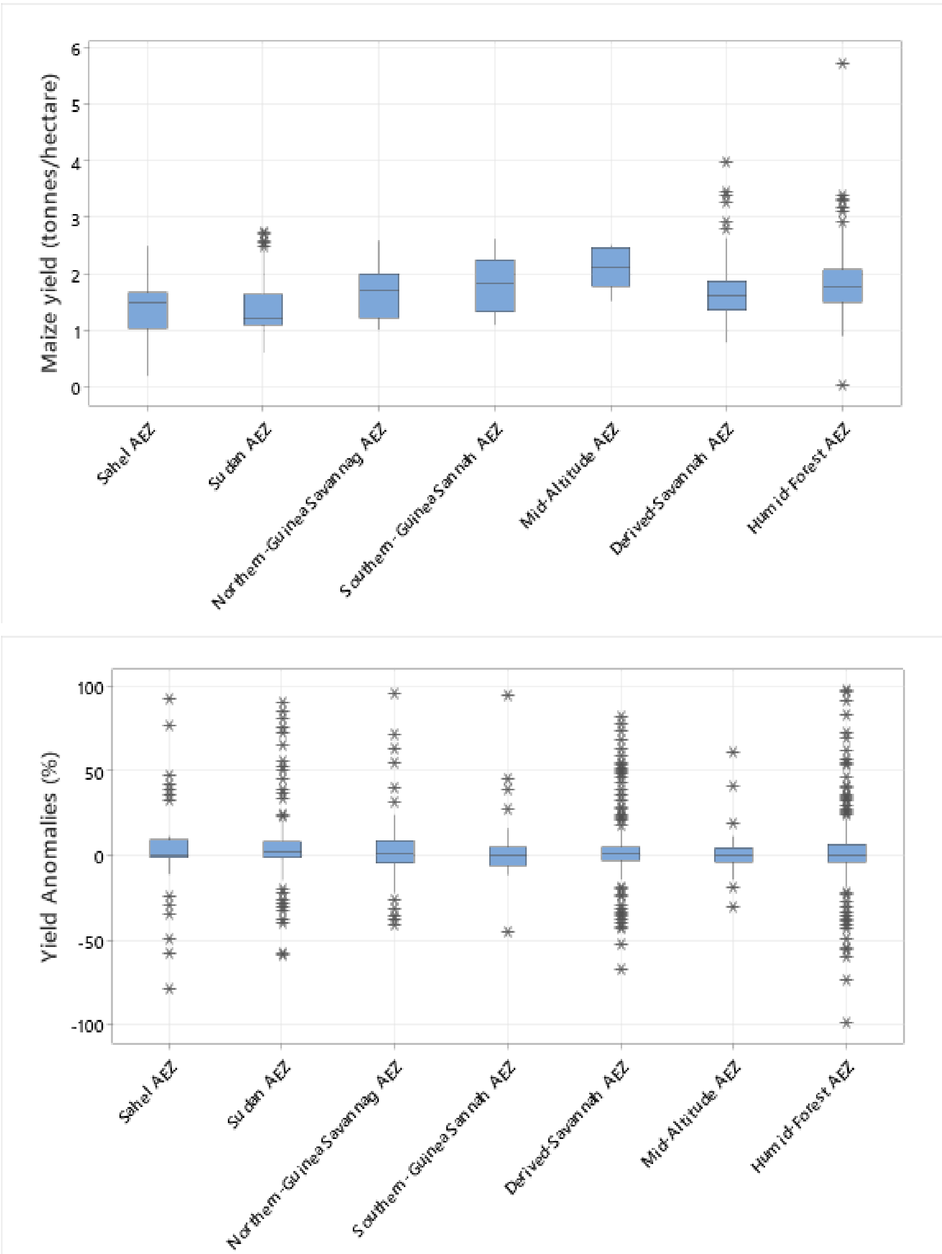
The box and whisker plot are employed in the descriptive statistical analysis of the maize yield across the agroecological zones as it offers a pictorial summary of important dataset characteristics including the central tendency, dispersion, asymmetry, and extremes, arrived at through percentile rank. As stated in the methodology section, the initial phase of a weather-impact analysis involves identifying trends to eliminate non-weather influences in the maize yield dataset. Figure 3a. displays the maize yield range across different agroecological zones while Figure 3b shows the detrended maize yield anomaly.

Figure 3a. demonstrates that the states located in the mid-altitude zone consistently achieved the highest maize yields per hectare, with an Interquartile Range (IQR) spanning from 1.9 to

2.35 metric tonnes per hectare. Following closely were the states in the Southern Guinea zone, where the IQR ranged from 1.2 to 2.2 metric tonnes per hectare, and the states in the Humid-Forest zone, with an IQR of 1.5 to 2.1 metric tonnes per hectare. States in the Northern Guinea Savannah zone had an IQR from 1.3 to 2.0 metric tonnes per hectare, while states in the Derived Guinea Savannah zone showed an IQR ranging from 1.5 to 1.9 metric tonnes per hectare. States in the Sudan zone recorded an IQR between 1.09 and 1.56 metric tonnes per hectare. Lastly, states in the Sahel zone displayed an IQR spanning from 1.02 to 1.59 metric tonnes per hectare. Notably, the Sudan showed a lower median yield value of 1.2 metric tonnes per hectare, while the Sahel showed a median yield of 1.45 metric tonnes per hectare. This is in spite of the Sahel having a lower IQR range than the Sudan.
Historically, the majority of maize grain production in Nigeria was concentrated in the southern region, particularly states like Oyo, Ogun, and Osun. [32], reported that approximately 50% of Nigeria's maize came from western Nigeria, with the remaining 50% divided between the North and the East. However, reports have shown that there has been a significant shift in dry grain production towards the savanna regions, particularly the Middle Belt region. States such as Benue, Nasarawa, Plateau, and Niger in the Middle Belt are renowned for their fertile soils and favourable climate for maize cultivation, leading to impressive yields. This area is now considered the primary maize belt of Nigeria. This trend could be attributed to factors such as the availability of streak-resistant varieties suitable for all ecological zones in Nigeria, the presence of high-yielding hybrid varieties, rising demand for maize, and the federal government's ban on rice, maize, and wheat imports.

Utilizing maize yield per unit area provides a valuable means of comparing productivity levels across diverse regions and agricultural practices. Standardizing measurements to a per-hectare basis allows for a consistent assessment of maize production efficiency and performance. Nevertheless, the superior approach for comparing crop production areas involves detrending the crop yield data. This detrending method helps in isolating the influence of weather and climate variables, eliminating non-weather-related factors, ensuring data consistency, and enabling more accurate trend detection and regional comparisons. The MYAI was employed to detrend the data, removing long-term trends and seasonality from the time series maize yield data. This process enables us to eliminate the overall yield increase resulting from recent technological advancements, attributing the residual impact primarily to climate disruptions [30], [33]. In contrast, Figure 4.2b illustrates the natural dispersion and variability of yield anomalies within different agroecological zones. Notably, the Mid-altitude agroecological zone exhibits lower dispersion, indicating reduced sensitivity to weather or lower inter-annual variability. It, however, displays more positive extreme values, suggesting enhanced yield performance in the region. Conversely, the Humid Monsoon Zone (HMZ) and the Sahel Agroecological Zone (SAZ) exhibit the greatest inter-annual variability, implying heightened sensitivity to weather fluctuations and higher year-to-year yield variations. On the contrary, the Southern Guinea Zone (SGZ), Derived Savannah Zone (DRZ), and Northern Guinea Savannah

Zone (NGZ) present comparable natural variability, indicating similar sensitivity to weather changes and consistent year-to-year yield fluctuations in these regions



(a)

(b)

Figure 3 Boxplots of (a) maize yield and (b) maize yield anomalies of states located in the seven agroecological zones

3.2 Best predictors classification, depending on the production areas

The database for this study comprises a total of ninety-eight potential weather predictors. This section of the report is dedicated to assessing and quantifying the relationships between these various weather indicators and yield anomalies, categorized by specific agroecological zones.

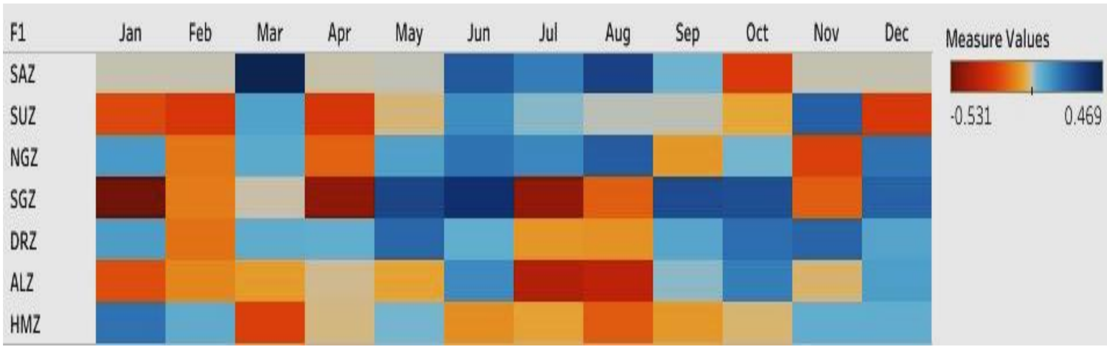
Within each zone, the weather indicators exhibiting the strongest correlations are ranked, underscoring their significance. These correlations are visually represented on the heat map in Figure 4, with blue denoting positive correlations and red indicating negative correlations.

In the mid-altitude zone, the correlations unveil that yield anomalies in this region exhibit comparatively lower sensitivity to weather variations when juxtaposed with other zones. Examining the complex influence of climate change on crop yield in high latitudes reveals a dynamic and multifaceted scenario. While it is a widely acknowledged fact that high latitudes are undergoing accelerated warming in comparison to other regions, the specific impacts on maize yield manifest variability. Likewise, in the Sahel region, the correlation analysis underscores the pivotal importance of climatic data, especially the rainfall occurring in the month of March. This time aligns with the maize planting season, making it a critical juncture in the crop's growth cycle. The successful establishment of a robust and healthy crop during March serves as a foundational element for potentially achieving higher maize yields. Favourable meteorological conditions during this crucial phase contribute to improved crop establishment, increased plant populations, and overall enhanced plant health, collectively contributing to greater maize yields at harvest time.

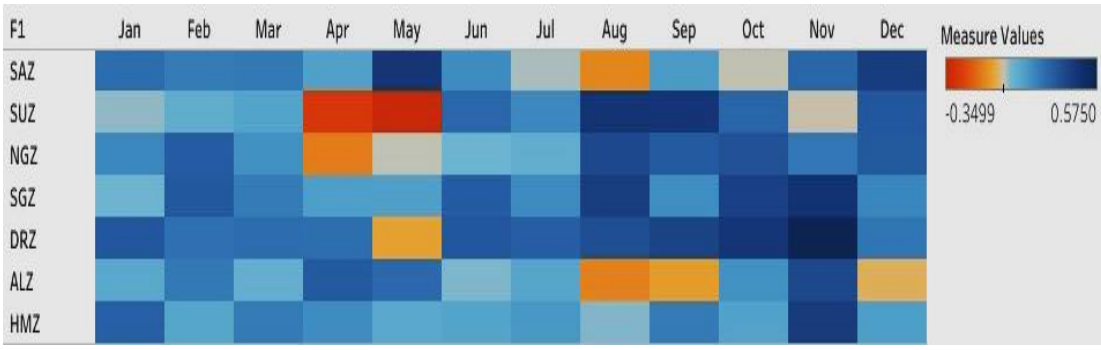
Empirical observations reveal that SPI(March) accounts for as much as 62% of the variability in maize yield anomalies within the Sahel region. Similarly, in the Humid Forest zone, the maximum temperature in March plays a crucial role in explaining up to 54% of the variability in maize yield. Notably, a noticeable negative correlation is observed for SPI(September), signifying the potential adverse effects of excessive rainfall on maize yield, particularly during the harvest period. This aligns with the findings of [5], who reported substantial yield losses in various states in the Midwest of the USA, such as Iowa, Minnesota, and Missouri, due to excessive rainfall, emphasizing the significant impact of flooding on maize yield loss, which can rival the impact of drought in specific regions.

Additionally, it is discernible that correlations of minimum temperature generally exhibit slightly higher values in comparison to other indices. While maximum temperature also influences maize yield by affecting factors such as photosynthesis, water stress, and heat stress, the influence of minimum temperature on critical growth stages and physiological processes makes it especially vital for determining overall yield. Maize, as a warm-season crop, thrives under relatively warm conditions, and a minimum daily temperature of 10°C is essential for seed germination. Optimal maize performance typically necessitates moderate temperatures ranging from 26°C to 29°C.

Monthly rainfall inputs predominantly yield varied correlation coefficients, ranging from negative 0.531 to 0.469. In the Humid Forest zone, the potential for excessive rainfall leading to negative anomalies during critical periods, especially in July, August, and September, is clearly demonstrated. In contrast, the Sahel exhibits a positive correlation with rainfall. Correlations related to minimum temperature are more positive, ranging from -negative 0.3499 to 0.5750, implying that increasing minimum temperatures may lead to more positive yield anomalies. Elevating minimum temperatures within the optimal range, typically between 25°C and 35°C, fosters maize development by extending the growing season, potentially boosting yields by enabling maize to complete its growth cycle and produce more grain. Notably, while an increase in maximum temperature in the Humid Forest zone results in a positive correlation, it gives rise to negative correlations in the Sahel. The Sahel region is more vulnerable to heat stress and water scarcity, potentially leading to reduced yields, whereas in the Humid Forest region, an increase in maximum temperatures can create conditions more favourable for certain diseases and pests that can harm maize crops and may also extend the growing season. In summary, rain-based indices are often less reliable predictors, while temperature-based indices prove to be more effective in the southern zones, as opposed to rainfall, which prevails as the dominant predictor in the northern zone



(a)



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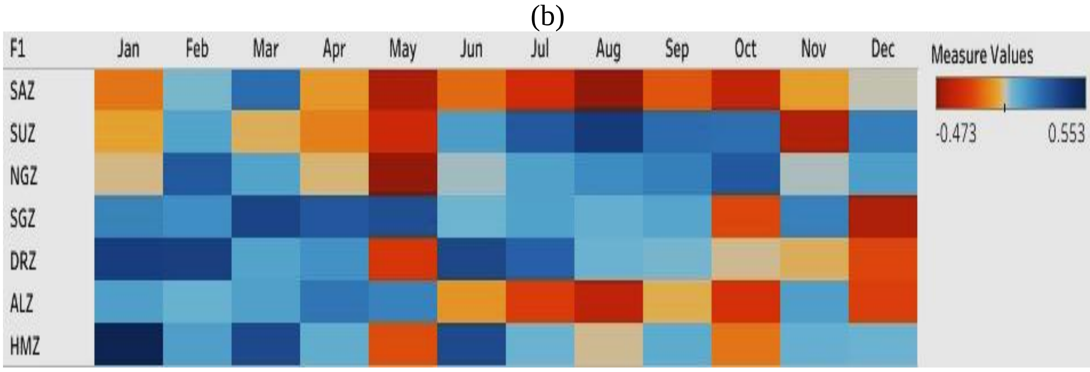

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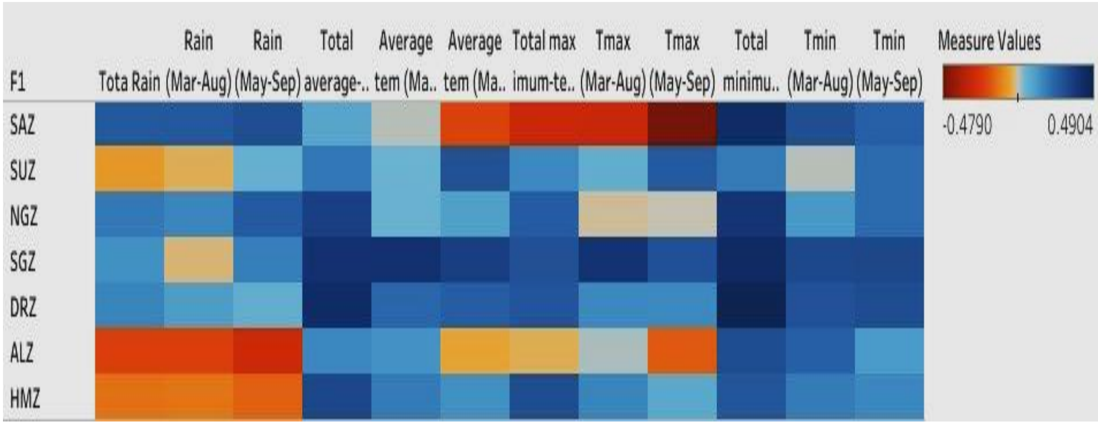

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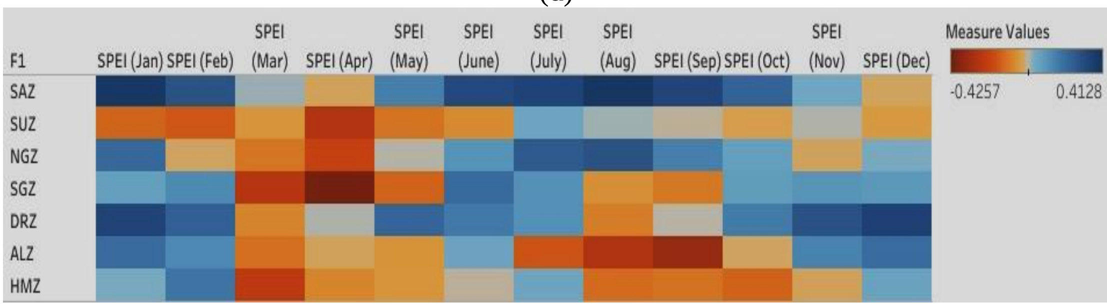

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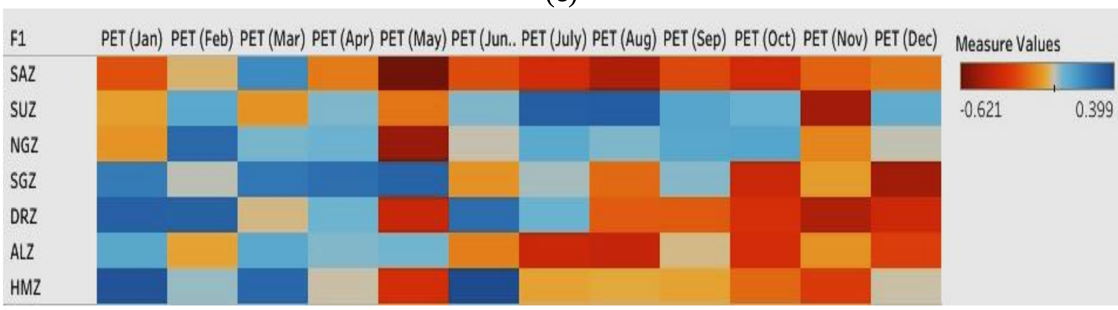


(f)

Figure 4 Correlation Heat Map within the zones for (a) rain (b)Tmin (c) average temperature (d) Seasonal climate (e) SPEI (f) PET

3.3 Yield forecast improvement using agroclimatic indices

The dataset at our disposal spans twenty-five years of critical agricultural data (See Appendices). To construct a robust learning set, we randomly select twenty years, constituting 80% of the available data, while the remaining five years are allocated for the test set. Table 2; shows the selected regression inputs for the multiple linear regressions based on the stepwise-Regression Criteria as discussed in section 2.5 above. Our objective is to assess and compare the forecasting capabilities of different configurations, denoted as (W1-5) and (I), within each distinct agroecological zone. Table 3, a crucial source of insight, offers a comprehensive view of our findings. It presents the coefficient of determination (R^2), correlation, and Mean Absolute Error (MAE) during the test period. Notably, as we delve into these configurations, we observe a noteworthy increase in the percentage of yield variance that can be explained by weather inputs. For example, in the Sahel region, where the R^2 climbs from a modest 0.2 to a significantly improved 0.8 when transitioning from the (W) to (I) configuration. This shift underscores the substantial impact of incorporating agroclimatic indices alongside direct weather data. It is important to note that these outcomes are not merely theoretical. Studies such as the work of [34], has indicated that, on a global scale, climate variations contribute to a third of the variability in crop yields. Our results align with these real-world observations, demonstrating the potential of well-selected agroclimatic indices to approach this level of explanatory power. By moving beyond simple weather data and embracing a more holistic approach, we take a significant stride toward enhancing the precision and reliability of crop yield forecasts.

Table 2 Input selection based on Stepwise- regression

Model Summary Stepwise Training			
Model	**R**	**R^2**	**Predictors**
Sahel	0.832	0.692	ACI. 65, ACI. 75, ACI. 61, ACI. 80
Sudan	0.947	0.896	ACI. 71, ACI. 36, ACI. 29, ACI. 73, ACI. 4
Northern Guinea Savannah	0.955	0.913	ACI. 38, ACI. 88, ACI. 48, ACI. 96, ACI. 21, ACI. 26
Southern Guinea Savannah	0.979	0.958	ACI. 1, ACI. 70, ACI. 21, ACI. 16, ACI. 80, ACI. 44, ACI. 36, ACI. 92, ACI. 40
Derived Guinea Savannah	0.686	0.470	ACI. 44, ACI. 96
Mid-Altitude	0.764	0.583	ACI. 81, ACI. 70, ACI. 67, ACI. 5
Humid Forest	0.678	0.459	ACI. 3, ACI. 44

Table 3: Testing MYAI predictors selected for different input configurations

Configurations	**I**		**W1**		**W2**		**W3**		**W4**		**Wn**	
Error metric	MAE	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE	R^2
SAZ	1.5	0.8	2.6	0.1	2.7	0.0	2.7	0.1	2.5	0.2	1.9	0.2
SUZ	1.1	0.5	2.9	0.0	2.6	0.1	2.6	0.0	2.5	0.1	2.3	0.2
NGZ	1.0	0.7	2.6	0.1	2.4	0.1	2.6	0.0	2.3	0.2	2.2	0.2
SGZ	0.6	0.8	2.8	0.0	2.7	0.2	2.6	0.1	2.7	0.2	2.7	0.2
DRZ	2.1	0.4	2.6	0.0	2.3	0.3	2.4	0.2	2.3	0.4	2.2	0.3
ALZ	1.8	0.6	3.0	0.0	3.1	0.0	3.2	0.0	3.1	0.1	2.7	0.2
HMZ	3.7	0.3	9.4	0.0	2.5	0.1	2.6	0.0	2.6	0.1	2.6	0.1

3.4 Forecast Impact of climate change on maize yield in Nigeria

MYAI quantifies the deviation from the anticipated year-to-year performance of maize yield. While crop yield represents the actual quantity of crops harvested, the crop yield anomaly quantifies the extent to which the actual yield differs from what was expected or considered typical. This anomaly can manifest as either positive, signifying a yield surpassing expectations, or negative, suggesting a yield that falls short of expectations. It is influenced by a multitude of factors, including weather conditions like droughts, floods, or extreme temperature events, as well as various environmental variables such as soil quality and nutrient availability. In this section, forecast of the MYAI for the years 2020-2050 under RCP4.5 and RCp8.5 is made, we explore the influence of the shifting climate patterns on maize yield anomalies using the multiple linear regression approach with the specified Configuration I, as detailed in the preceding section.

Historically, the MYAI in the Sahel has predominantly exhibited negative anomalies, with an average value of -1.12 (Figure 5a). The regression models reveals that these negative anomalies can primarily be attributed to two key factors: insufficient rainfall and elevated PET levels in the month of March. The forecast for maize yield anomalies in the Sahel region paints a promising picture for the future. Considering RCP scenarios, it becomes evident that the region's agricultural outlook for production of maize is set to improve. Under RCP4.5, specifically, there is a notable reduction in the PET levels during the critical month of March. This decrease in PET translates to a higher potential for maize production in the area, hinting at a positive anomaly. Conversely, under the RCP8.5 scenario, the forecast also displays a positive anomaly. It suggests that the region will experience more favourable conditions for maize cultivation. The relationship between temperature and maize yield in the Sahel region is complex and influenced by various factors. While a higher minimum temperature can have some positive effects on maize yield, it is not the sole determining factor. According to [35], warmer temperatures can have both positive and negative impacts on maize yield, depending on the availability of soil moisture. Therefore, if temperatures in the Sahel region increase and there is adequate water availability, it has the potential to positively affect maize yield. Additionally, research conducted by [36] also reveals that both the direct and overall effects of temperature and precipitation have notably positive outcomes. An increase in temperature or precipitation is projected to significantly enhance maize.

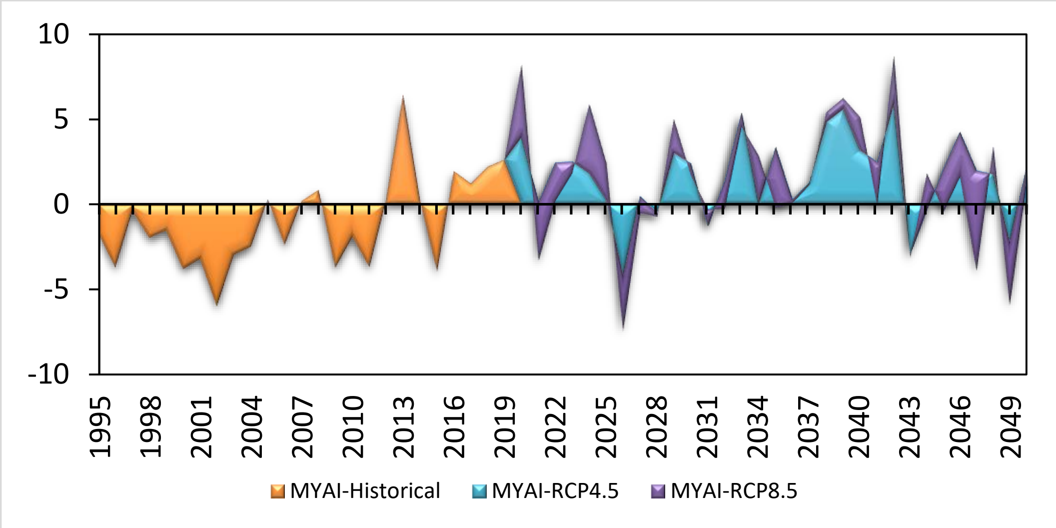
During the training period, a negative anomaly of -1.38 was documented in Sudan. This adverse anomaly can predominantly be attributed to the minimum temperature in September and the amount of rainfall in August. Reduced levels of minimum temperatures in September during maize growing season, negatively affect maize yields by disrupting crucial growth stages, causing delayed germination, and uneven plant development. Interestingly, in the context of climate change, the increased warming conditions observed in Sudan hold the potential for a positive impact on maize production. Consequently, under the Representative Concentration Pathway (RCP) 8.5 scenario, maize yield potential is projected to be positive, with an average value of 5.31. The higher temperatures anticipated under RCP8.5 are expected to create more favourable conditions for maize cultivation in the region. Conversely, under the RCP4.5 scenario, where temperatures are projected to be less warm, the maize potential turns negative, with an average value of -28.45. This calls for adaptation strategies in the region, particularly a shift in the planting date to align with the changing temperature conditions and maximize maize yields.

The northern Guinea savannah region has experienced a somewhat mild negative anomaly in maize yield, with an average value of -0.0581. Regression analysis show that the principal influencing factors of maize yield anomalies in this agroecological zone are the average temperature and the SPEI in the month of October. The regression models employed in this analysis have highlighted that, on the one hand, an increase in average temperatures significantly impacts maize yield. This is particularly noteworthy, as elevated temperatures can disrupt the growth and development of maize plants. However, the models also indicate that, on the other hand, a slight increase in rainfall, as indicated by higher SPEI values, can contribute positively to maize production. In the future, the potential for maize production in this region shows promise, under the tow RCP scenarios. Under these scenarios, the projections suggest an increased maize yield potential, with an average of 19 for RCP4.5 and 22 for RCP8.5. This reflects the positive impact of both temperature and precipitation changes anticipated under these climate scenarios. Nevertheless, it is crucial to exercise caution when interpreting these results. The region's elevated average temperatures, especially beyond a certain threshold, could pose risks to maize cultivation. These risks include heat stress, reduced water availability, and potential damage to maize plants. It's important to note that the regression model employed in this analysis may not account for these extreme temperature conditions, and additional factors like heat stress tolerance in maize varieties and adaptive farming practices must be considered to ensure the sustainability of maize production in the face of changing climatic conditions.

The historical maize yield anomaly in the southern Guinea savannah region showed a relatively minor negative potential, with an average value of -0.95. However, under RCP4.5 and RCP8.5, the anticipated future maize yield anomalies are significantly more negative, with values of -8.82 for RCP4.5 and -8.85 for RCP8.5. The regression models used to investigate these trends shed light on the key drivers of maize yield anomalies in the southern Guinea savannah. It is evident that rainfall in August, as indicated by the SPI and SPEI values for that month, exerts a significant influence on maize anomalies in this region. Additionally, the minimum temperature values in April play a substantial role in determining maize yield outcomes. Notably, the zone's susceptibility to excessive rainfall becomes apparent, as high rainfall values for the months of June, August, and September are associated with reduced maize yield potential. These excessive rainfalls can lead to waterlogged soil conditions, and increased disease pressure, all of which can have a detrimental impact on maize production. Conversely, higher temperature values in the month of April are correlated with an increase in maize yield. This positive relationship underscores the importance of temperature conditions during the early stages of maize growth and development.

In the derived savannah region, the regression models shows that certain climatic factors stand out as key drivers behind maize yield anomalies. Notably, higher minimum temperatures recorded in the month of November, along with SPEI values in December, emerge as the primary influencers of maize yield variations. The SPEI value in December, calculated over a three-month period encompassing October, November, and December, holds particular significance. This value is closely tied to the presence of adequate precipitation during the preceding months, ensuring sufficient soil moisture and water availability crucial for the development and maturation stages of maize crops. This period aligns with the typical growth cycle of maize in the region and plays a pivotal role in determining maize performance. However, under climate forecasts indicate a reduction in rainfall, which, in the context of the maize crop, translates to decreased potential. As the region faces a scenario of diminished rainfall, the capacity for maize production is significantly compromised. Quantitatively, the maize yield anomaly forecasts for the derived savannah region historically, experienced an average anomaly of -1.23. However, under the climate change scenarios the forecasts indicate a shift towards significantly more negative values, with an average anomaly of -4.92 under RCP4.5 and -5.4 under RCP8.5. Underscoring the pressing need for adaptation strategies to mitigate the impact of changing climatic conditions on maize production in this region.

In the mid-altitude zone of Nigeria, rainfall is generally available during the growing season for maize. The most significant threat to crop performance in these areas is often associated with excessive rainfall. This challenging scenario is effectively captured by our regression model, which highlights that the overabundance of rainfall during the crucial growing season, particularly as indicated by the SPI values in September, is closely correlated with a reduction in maize yield potential for the region. Also, our analysis reveals that lower PET values for the months of July and October are closely linked to reduced maize yield anomalies. Lower PET implies that there is diminished atmospheric demand for moisture, leading to decreased transpiration – the process by which maize plants absorb water from the soil and release it into the atmosphere. This disruption in transpiration hinders the uptake of essential nutrients and moisture by maize plants, resulting in stunted growth and a reduction in their overall yield potential. Under climate change the regression models forecasts a significant alteration in maize yield anomalies. Historically, the region has maintained an average yield anomaly of 0.12. The forecasts indicate a transition from this mildly positive anomaly to a distinctly negative one. Specifically, under RCP4.5, the maize yield anomaly is projected to plummet to -17.17, while under RCP8.5, it is anticipated to decrease to -6.32. This shift can be attributed to the increasing prevalence of high rainfall values resulting from climate change, which poses a formidable challenge to the region's maize production.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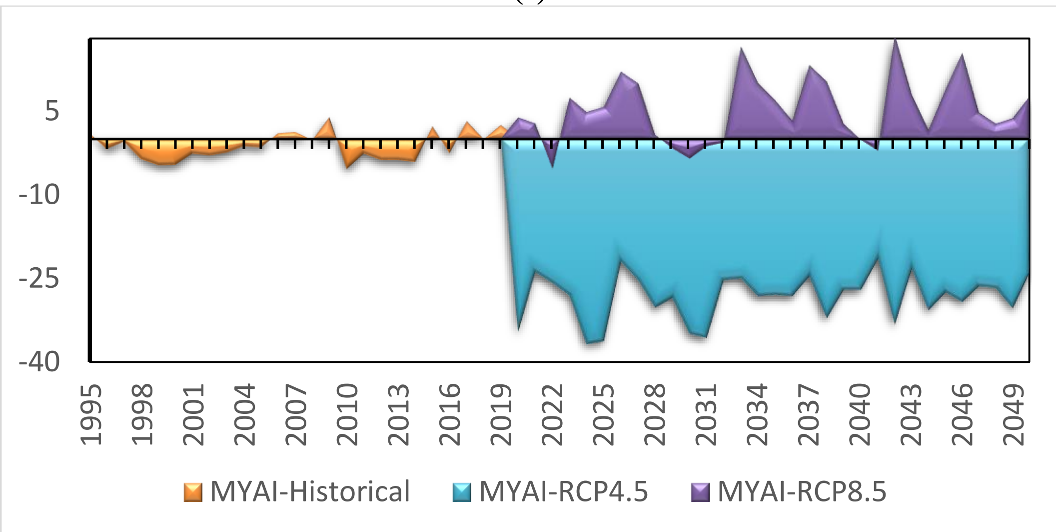
MYAI-Historical
MYAI-RCP4.5
MYAI-RCP8.5

(a)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MYAI-Historical
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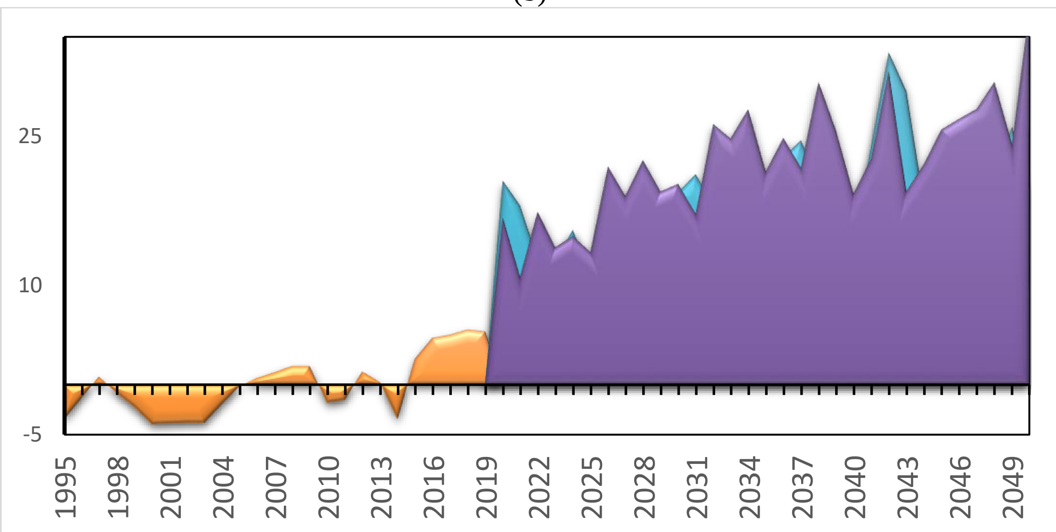
MYAI-RCP8.5

(b)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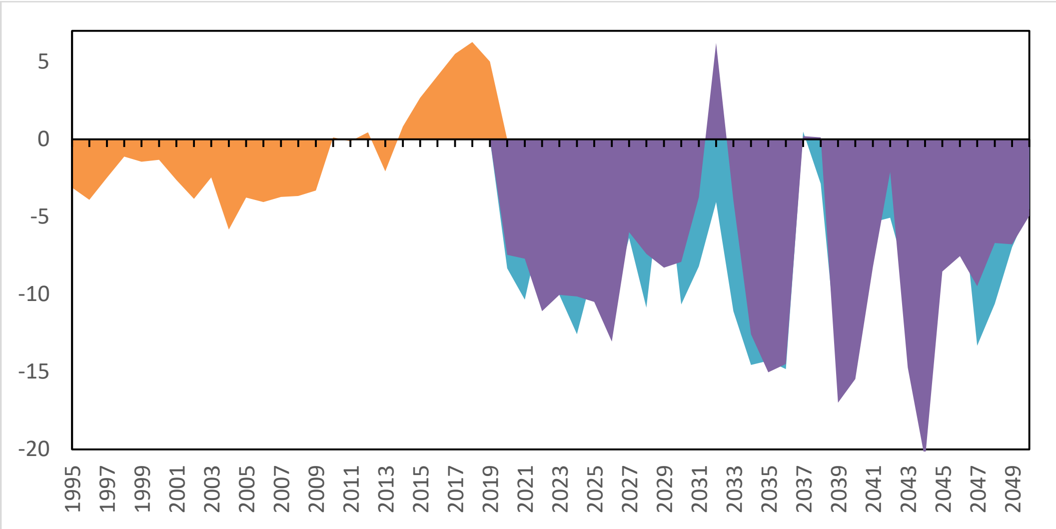
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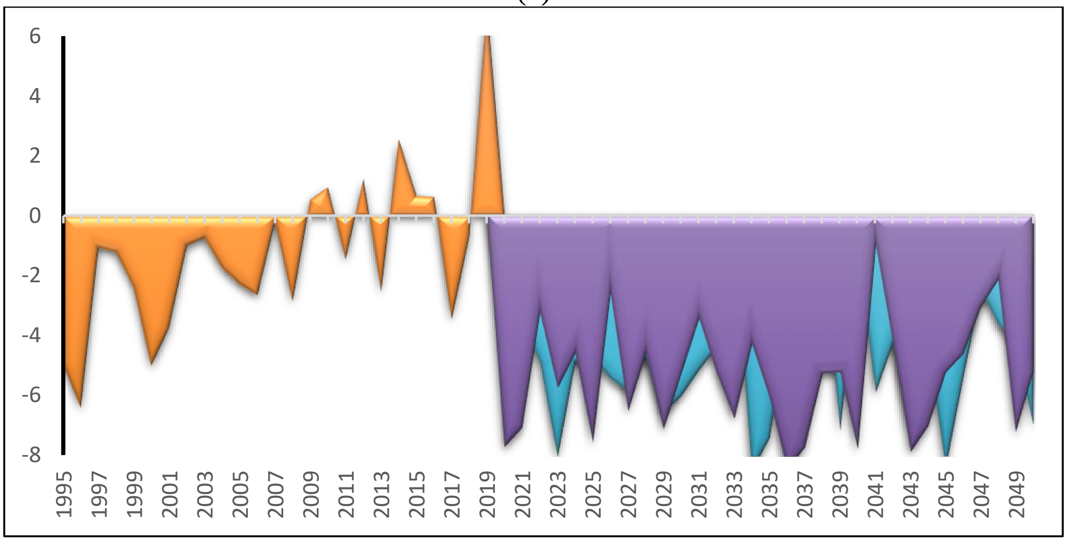
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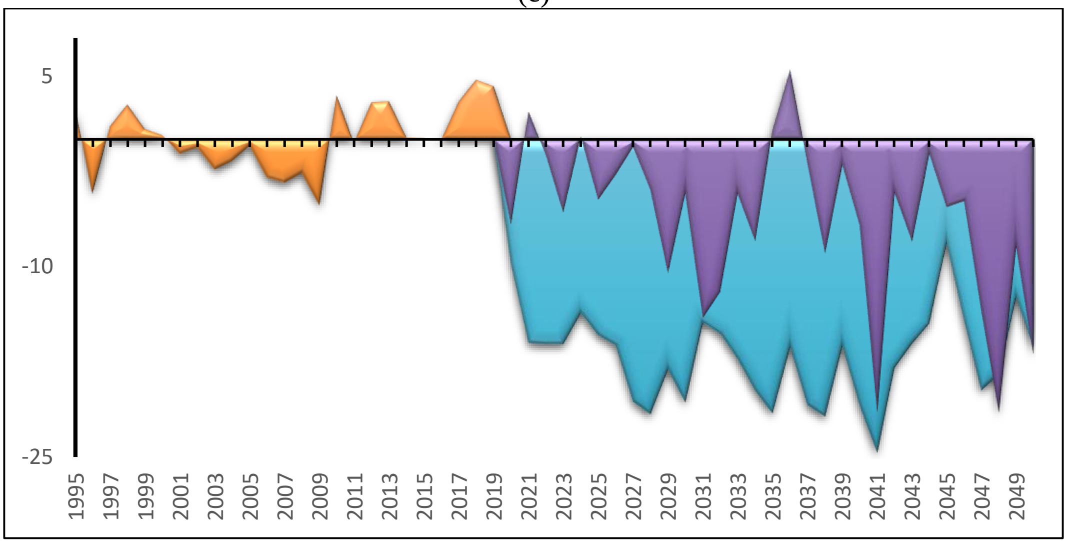
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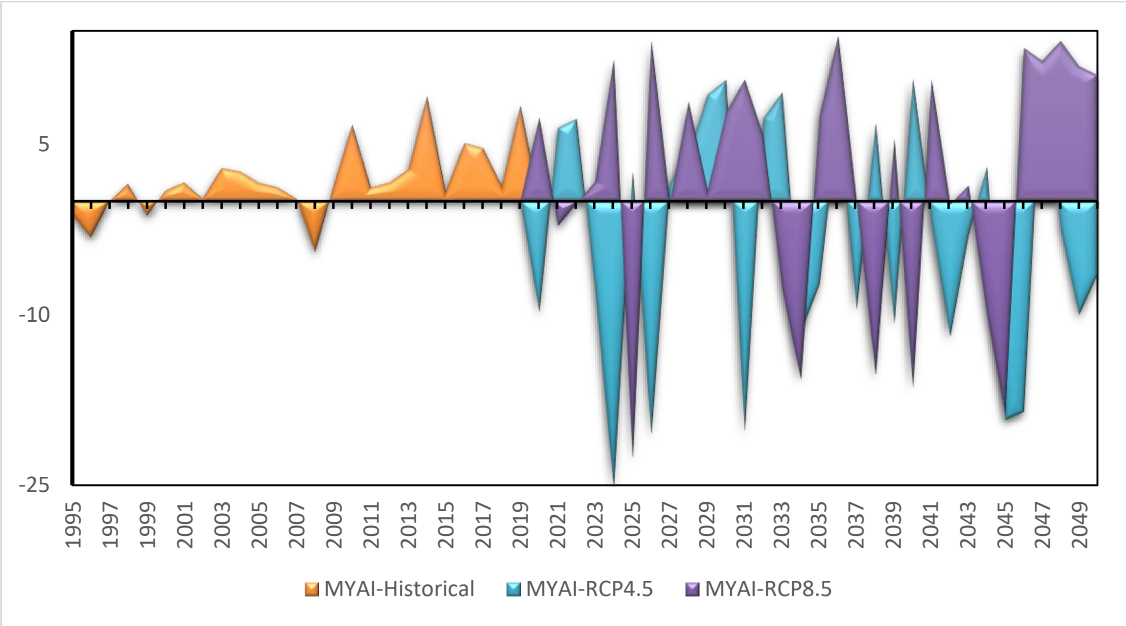
(f)



(g)

Figure 5. Forecast of MYAI for historical (1995-2019) and Future (2020-2050) under RCP4.5 and RCP8.5 in the (a) Sahel (b) Sudan (c) Northern Guinea Savannah (d) Southern Guinea Savannah (e) Derived Guinea Svannah (f) Mid-altitude and (g) Humid Forest Agroecological zones

4.0 Conclusions

In conclusion, this study has provided valuable insights into the complex relationship between climate, agroclimatic indices, and maize yield in Nigeria, with a particular focus on different agroecological zones. Climate change and its potential impact on crop production have been a central concern, as shifts in weather patterns and temperature variations are expected to significantly influence agricultural productivity. The findings of this research underscore the importance of understanding the specific factors affecting crop yield, as these factors can vary across regions.

The analysis of historical data revealed that different agroecological zones in Nigeria exhibit varying levels of sensitivity to weather variations. For instance, the Sahel region showed a strong correlation between rainfall in March and maize yield, suggesting the critical role of climate in determining crop outcomes. In contrast, the mid-altitude zone was more affected by excessive rainfall during the growing season. The study also highlighted the significance of minimum temperature and its impact on crop development, particularly in areas with moderate temperature ranges. Moreover, the incorporation of agroclimatic indices into crop yield forecasting models proved to enhance the accuracy and reliability of predictions. By moving beyond simple weather data and considering a broader range of climate-related factors, the study demonstrated the potential for more precise crop yield forecasts, which can assist in planning and decision-making for agricultural practices.

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APPENDIX

Table 1. List of Agroclimatic Indices used in this study

ACI	PERIOD	NAME
1	JAN	Sum of RAIN
2	JAN	Average of TMEAN
3	JAN	Average of TMAX
4	JAN	Average of TMIN
5	FEB	Sum of RAIN
6	FEB	Average of TMEAN
7	FEB	Average of TMAX
8	FEB	Average of TMIN
9	MAR	Sum of RAIN
10	MAR	Average of TMEAN
11	MAR	Average of TMAX
12	MAR	Average of TMIN
13	APR	Sum of RAIN
14	APR	Average of TMEAN
15	APR	Average of TMAX
16	APR	Average of TMIN
17	MAY	Sum of RAIN
18	MAY	Average of TMEAN
19	MAY	Average of TMAX
20	MAY	Average of TMIN
21	JUN	Sum of RAIN
22	JUN	Average of TMEAN
23	JUN	Average of TMAX
24	JUN	Average of TMIN
25	JUL	Sum of RAIN
26	JUL	Average of TMEAN
27	JUL	Average of TMAX
28	JUL	Average of TMIN
29	AUG	Sum of RAIN

30	AUG	Average of TMEAN
31	AUG	Average of TMAX
32	AUG	Average of TMIN
33	SEP	Sum of RAIN
34	SEP	Average of TMEAN
35	SEP	Average of TMAX
36	SEP	Average of TMIN
37	OCT	Sum of RAIN
38	OCT	Average of TMEAN
39	OCT	Average of TMAX
40	OCT	Average of TMIN
41	NOV	Sum of RAIN
42	NOV	Average of TMEAN
43	NOV	Average of TMAX
44	NOV	Average of TMIN
45	DEC	Sum of RAIN
46	DEC	Average of TMEAN
47	DEC	Average of TMAX
48	DEC	Average of TMIN
49	ANNUAL	Total Sum of RAIN
50	ANNUAL	Total Average of TMEAN
51	ANNUAL	Total Average of TMAX
52	ANNUAL	Total Average of TMIN
53	(Mar-Aug)	Maize crop season Rainfall (south)
54	(Mar-Aug)	Maize crop season Tmax (south)
55	(Mar-Aug)	Maize crop season Tmin (south)
56	(Mar-Aug)	Maize crop season Tmean (south)
57	(May-Sept)	Maize crop season Rainfall (north)
58	(May-Sept)	Maize crop season Tmax (north)
59	(May-Sept)	Maize crop season Tmin(north)
60	(Mar-Aug)	Maize crop season Tmean (north)
61	Jan	PET
62	Feb	PET
63	Mar	PET
64	Apr	PET
65	May	PET
66	Jun	PET
67	Jul	PET
68	Aug	PET
69	Sep	PET
70	Oct	PET
71	Nov	PET

72	Dec	PET
73	Jan	SPI
74	Feb	SPI
75	Mar	SPI
76	Apr	SPI
77	May	SPI
78	Jun	SPI
79	Jul	SPI
80	Aug	SPI
81	Sep	SPI
82	Oct	SPI
83	Nov	SPI
84	Dec	SPI
85	Jan	SPEI
86	Feb	SPEI
87	Mar	SPEI
88	Apr	SPEI
89	May	SPEI
90	Jun	SPEI
91	Jul	SPEI
92	Aug	SPEI
93	Sep	SPEI
94	Oct	SPEI
95	Nov	SPEI
96	Dec	SPEI
97	ANNUAL	SEASONALITY INDEX
98	ANNUAL	HYDROLOGIC RATIO