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Climate Change, Environmental Degradation, and Food Security in Nigeria: A Machine Learning Analysis

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ABSTRACT

Climate change, which arises from the activities of humans, leads to increased temperature and irregular rainfall patterns, which pose a significant threat to food security, particularly in developing nations like Nigeria, where agriculture is critical to the economy and livelihood. Environmental degradation, exacerbated by climate change, further complicates this scenario by reducing arable land, depleting water resources, and altering weather patterns, all of which contribute to decreased agricultural productivity. The current study aims to assess the impacts of the dual challenges of climate change and environmental degradation on food security in Nigeria, using quarterly time series data from 1991 Q1 to 2023 Q4. The research employs multiple machine learning algorithms, including Multiple Linear Regression, K-Nearest Neighbor (K-NN), Support Vector Regression, and Random Forest, to model the complex relationships between climate variables (CO_2 emissions, temperature anomalies) and food production index (FPI), a proxy for food security. The results indicated that CO_2 emissions and temperature anomalies have a significant negative effect on agricultural productivity, while land use and fertilizer consumption positively influence food production. The study concluded that sustainable land management practices, climate-resilient agricultural methods, and investment in agricultural infrastructure are critical to mitigating the adverse effects of climate change on food security. Policy recommendations were made to enhance resilience in Nigeria's agricultural sector.

Keywords: Climate Change; Environmental Degradation; Food Security; Machine Learning; Agricultural Productivity; Nigeria

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1. Introduction

Climate change and environmental degradation have emerged as pivotal challenges confronting nations worldwide, with profound implications for food security. In Nigeria, a country characterized by a population exceeding 200 million and a substantial dependence on agriculture for economic sustenance and employment, the impacts of these phenomena are particularly acute [1]. Agriculture is not merely an economic activity; it is the backbone of rural livelihoods, contributing significantly to the nation's gross domestic product (GDP) and serving as a primary source of food for the majority of the population. However, the increasing variability of climate patterns, coupled with persistent environmental degradation, poses significant threats to agricultural productivity, thus endangering food security for millions of Nigerians [2].

The nexus relationship between climate change and food security is increasingly evident, particularly in Nigeria's diverse agro-ecological zones. As one of Africa's most populous countries, Nigeria faces unique challenges stemming from its dependence on agriculture, which employs approximately 70% of its workforce and contributes significantly to the nation's GDP [3]. However, the interplay of climate variability, deforestation, soil erosion, and water scarcity has exacerbated the vulnerability of agricultural systems, jeopardizing food production and access [4].

The country has experienced significant shifts in temperature and precipitation patterns, leading to altered growing seasons and increased instances of droughts and floods. For instance, studies have shown that average temperatures in Nigeria have risen by approximately 1.2 degrees Celsius over the past century, a trend that is projected to continue [5]. These climatic changes adversely affect crop yields, particularly for staple foods such as maize, rice, and cassava, which are critical for both local consumption and export. The declining productivity of these essential crops directly threatens food availability, leading to higher prices and increased vulnerability among low-income households [6].

Environmental degradation significantly intensifies the myriad challenges posed by climate change, creating a complex interplay that undermines agricultural sustainability. The degradation of vital natural resources, primarily resulting from deforestation, soil erosion, and land degradation, has severely compromised the ecological balance that is essential for implementing sustainable agricultural practices [7]. This ecological imbalance disrupts the natural systems that support crop growth and soil health, ultimately threatening food security. According to the Food and Agriculture Organization (FAO), Nigeria has alarmingly lost approximately 40% of its forest cover over the last three decades. This dramatic loss can be attributed primarily to factors such as agricultural expansion, logging activities, and rapid urbanization. The consequences of deforestation extend beyond the immediate loss of trees; they contribute to increased greenhouse gas emissions, which exacerbate climate change and further destabilize the environment [8].

Soil degradation has also emerged as a pressing issue, characterized by nutrient depletion, reduced fertility, and the loss of organic matter. This widespread degradation has become rampant across many regions in Nigeria, adversely impacting farmers' ability to maintain productive lands [1]. The declining soil health not only limits the quantity and quality of crop yields but also poses significant challenges for farmers striving to sustain their livelihoods. As soils become increasingly degraded, the ability to implement effective agricultural practices diminishes, resulting in a cycle of reduced productivity and heightened vulnerability to food insecurity.

The implications of climate change and environmental degradation on food security are further compounded by socioeconomic factors, including poverty, population growth, and limited access to technology. With an annual population growth rate of about 2.6%, Nigeria's demand for food is expected to increase significantly in the coming decades [9]. However, the ability of the agricultural sector to meet this demand is hindered by the dual challenges of climate change and environmental degradation. Many smallholder farmers, who represent the majority of agricultural producers in Nigeria, often lack the resources and knowledge to implement adaptive practices or invest in sustainable technologies. Consequently, these farmers are particularly vulnerable to climate-related shocks, making them susceptible to food insecurity and malnutrition [2].

As Nigeria grapples with the dual challenges of climate change and environmental degradation, there is an urgent need for comprehensive policies that not only address immediate food security concerns but also promote long-term sustainability in agricultural practices [7]. Therefore, this study aims to assess the impact of climate change and environmental degradation on food security in Nigeria to make policy recommendations. The novelty of this study lies in its use of machine learning (ML) techniques, such as K-Nearest Neighbours (K-NN), Support Vector Regression (SVR), and Random Forest, to model the complex, non-linear interactions between climate change, environmental degradation, and food security in Nigeria. Traditional econometric models, like Multiple Linear Regression (MLR), typically assume linear relationships and fail to capture the intricate, dynamic factors influencing agricultural productivity. This study, by utilizing advanced ML algorithms and a comprehensive quarterly time-series dataset (1991–2023), uncovers patterns that traditional methods overlook, such as how CO_2 emissions, temperature anomalies, and land use interact to affect food production.

This introduction section is followed by a Literature Review that discusses prior research gaps. The Materials and Methods section details the data and machine learning techniques used. The Experimentation and Results section presents statistical outcomes and graphical evaluations. The Discussion of Findings interprets the results, and the Conclusions section offers actionable policy suggestions to mitigate climate change's impact on food security in Nigeria.

2. Literature Review

Several studies have investigated the implications of climate change on food security and agricultural systems, particularly in the context of Nigeria. In a study that examined the implications of climate change on agricultural extension systems in Nigeria, specifically focusing on the impacts of extreme weather events between 2000 and 2018 [2]. Utilizing qualitative methods, the study revealed that climate change poses significant threats to agricultural productivity. The authors emphasized the necessity for resilience-building strategies to enhance the adaptive capacity of agricultural systems in response to these challenges. Pickson and Boateng analyzed the role of climate change in food security across 15 African countries, including Nigeria, during the period from 1970 to 2016 [9]. Employing the Mann-Kendall test, the researchers found that rainfall plays a significant role in influencing food security, while the effects of temperature were found to be more complex. This study underscores the importance of understanding the multifaceted impacts of climate variables on food security.

Ajetomobi, Abiodun, and Hassan utilized the Ricardian model to assess the economic impact of climate change on Nigerian agriculture [10]. Their findings revealed that increasing temperatures and declining rainfall substantially reduced crop yields and farm revenues. The authors projected that without adaptation measures, agricultural productivity could decline by up to 30% by 2050, posing a severe threat to food security. Similarly, Oluwatayo and Ojo explored the relationship between economic growth, poverty, and food security in sub-Saharan Africa, focusing on Nigeria [11]. Using panel data analysis, they found that while economic growth had a positive effect on food security, environmental degradation and climate variability offset these gains, particularly for rural households.

Adewuyi and Olofin conducted a spatio-temporal analysis of land use and urban sprawl in Sokoto, Nigeria [12], between 1986 and 2016. Their study revealed significant urban expansion, which occurred at the expense of agricultural land, thereby exerting pressure on food production areas. Elum, Modise, and Marr examined farmers' perceptions of climate change and adaptive strategies in South Africa [13]. Although the study focused on South Africa, the findings applied to Nigeria, as they demonstrated that farmers' perceptions of climate change were aligned with meteorological data, and access to information and resources significantly influenced their adaptation strategies.

In a related study, Obayelu, Adepoju, and Idowu used a multinomial logit model to analyze the factors influencing farmers' choices of adaptation strategies in Ekiti State, Nigeria [14]. They found that education level, farm size, access to credit, and access to climate information were key determinants of farmers' ability to adopt climate-resilient practices. Wijerathna-Yapa and Pathirana assessed soil erosion across Nigeria's agroecological zones [15], using GIS and remote sensing techniques. Their study revealed that over 50% of agricultural lands exceeded sustainable soil erosion rates, posing a significant threat to long-term food security.

Onyeneke et al. investigated the adoption of climate-smart agriculture (CSA) in southeastern Nigeria [16], revealing low adoption rates despite farmers' awareness of climate change impacts. Limited access to technology and inadequate policy support were cited as major barriers to CSA adoption. Ayanlade, Radeny, and Morton compared smallholder farmers' perceptions of climate change with meteorological data in southwestern Nigeria [17]. They found a strong correlation between farmers' perceptions and observed climate trends, underscoring the importance of integrating local knowledge into climate adaptation strategies.

Shiru et al. conducted a trend analysis of droughts during Nigeria's crop-growing seasons, applying the Standardized Precipitation Evapotranspiration Index (SPEI) to data from 1961 to 2010 [18]. The study revealed an increasing frequency and severity of droughts, particularly during critical crop-growing periods, with significant implications for agricultural productivity and food security. Matemilola and Elegbede provided a comprehensive review of the challenges to food security in Nigeria [19], emphasizing the role of climate change, environmental degradation, and socioeconomic factors. They recommended integrated policy approaches to address these challenges and enhance agricultural productivity and food security.

Atube et al. investigated the broader implications of climate change on food security [8], with a particular emphasis on smallholder agriculture. Their findings indicated that rising temperatures and changing rainfall patterns are major threats to food availability and access. This research highlights the vulnerability of smallholder farmers to climate change, which can undermine food systems and exacerbate food insecurity. Focusing on Northern Nigeria, Okunola and Ikuomola assessed the socio-economic impacts of desert encroachment resulting from climate change [7]. Their qualitative study revealed that climate-induced desertification has led to increased migration and communal conflicts over diminishing arable land. This finding points to the socio-political dimensions of food security challenges exacerbated by environmental degradation. Zakari, Ibro, Moussa and Abdoulaye discussed various adaptation strategies in response to the impacts of climate change on food security [3]. They highlighted the need for efficient agricultural practices and improved water management systems as critical components of adaptation efforts. The study emphasizes that implementing effective strategies can mitigate the adverse effects of climate change on food security.

The study by Chandio et al. investigates the short and long-run impacts of climate change on agricultural output in China from 1982 to 2014 [20], using various econometric approaches. Their analysis reveals that CO_2 emissions positively influence agricultural productivity in both the short and long run, while temperature and rainfall have negative long-term effects on output. Additionally, factors such as the land area under cereal crops, fertilizer consumption, and energy consumption were found to positively correlate with agricultural output in both time frames. The study's use of unit root tests confirmed the variables' stationarity, and the autoregressive distributed lag (ARDL) bounds testing approach demonstrated a significant relationship between climate variables and agricultural productivity. The error correction model highlighted a dynamic adjustment process in response to climatic shocks, indicating that deviations from long-run equilibrium are corrected over time. The authors stress the need for crop-specific and region-specific policy interventions in China to mitigate climate change effects on agriculture and ensure food security for a growing population.

A substantial body of studies indicates that rising temperatures adversely affect crop yields, while increased rainfall can enhance food availability. For instance, Appiah-Otoo et al. found that rainfall positively influences food access and availability in 25 Sub-Saharan African countries using a panel model [6].

Conversely, higher temperatures were shown to have detrimental effects on both food access and availability, highlighting the dual role of climate variables in influencing agricultural productivity. Gobezie and Boka demonstrated a strong correlation between higher greenhouse gas emissions and increased rates of malnutrition [4], thereby undermining food security in Sub-Saharan Africa. This finding underscores the importance of addressing emissions within the broader framework of food security strategies. Ughaelu highlighted that extreme weather events [5], such as floods and droughts, significantly disrupt agricultural productivity in Nigeria. The occurrence of these events often leads to considerable food shortages, compounding the challenges faced by vulnerable populations.

Ogundipe and Ogundipe. established an inverse relationship between environmental degradation and food production in Nigeria [1], illustrating that pollution and land degradation pose significant threats to food security. This degradation not only affects current agricultural productivity but also jeopardizes future food availability. Research consistently shows that higher income levels positively influence food security. However, as noted by Gobezie and Boka [4], economic growth can initially lead to increased environmental degradation, which may ultimately harm food security. This complex relationship necessitates careful management of economic advancements to prevent environmental harm. The relationship between population growth and food production is multifaceted and context-dependent. Ogundipe and Ogundipe. found negligible effects of population growth on food production in Nigeria [1], indicating that an increasing population does not necessarily correlate with a proportional enhancement in food supply. This finding underscores the importance of considering other factors, such as agricultural practices and technology, in determining food security.

The existing literature reviewed above highlights the negative impacts of climate change on food security, focusing mainly on temperature and rainfall. However, traditional econometric models used by these studies cannot capture the non-linear relationships between climate variables and agricultural productivity. Studies by Alhassan and Ajetomobi et al. highlight the significant role of climate factors but rely on linear approaches that oversimplify complex dynamics [2,10]. This study therefore, addresses these gaps by employing machine learning techniques such as K-Nearest Neighbour (K-NN), Support Vector Regression (SVR), and Random Forest, which in contrast to econometric models, which simplify the impacts of climate variables, machine learning enables the detection of non-linear dynamics that better reflect the realities of Nigeria's agricultural systems, where climate change and environmental degradation are critical factors [2]. The application of machine learning (ML) in this study is justified by its ability to integrate and analyze multiple environmental and agronomic variables to uncover patterns that are often beyond the reach of traditional econometric techniques. As illustrated by Kassanuk and Phasinam [21], ML algorithms are particularly well-suited for modeling complex, non-linear relationships within large and diverse datasets.

Additionally, the studies reviewed above justify the choice of climate variables such as CO_2 emissions, temperature anomalies, and land use as critical to understanding food security. While temperature and rainfall are often the focus, CO_2 emissions and temperature anomalies provide a more comprehensive view of climate impacts. CO_2 emissions contribute to environmental degradation, affecting soil and rainfall patterns, while temperature anomalies aggregate climate variations. This approach fills a gap left by previous studies, providing a more accurate, data-driven framework for assessing the impact of climate change on Nigeria's agricultural sector.

3. Materials and Methods

3.1. Model Specification and Data Description

This study adapted the model specification of Chandio et al. [20], a model designed to analyze the short and long-run impacts of climate change on agricultural production in China. Chandio et al.'s model was selected because it provides a comprehensive framework that incorporates key variables like CO_2 emissions, temperature, rainfall, land use, and fertilizer consumption, which are also critical for understanding Nigeria's agricultural productivity. Given that this model has proven effective in analyzing agricultural output in China, it serves as a strong foundation for the Nigerian context. The key difference is that the model was modified to include temperature anomalies specific to Nigeria's climate dynamics, which allows for a more accurate representation of climate impacts on food security in the Nigerian context. Chandio et al.'s model specification is as follows:

$$AGR_t = f(CO_{2t}, TEMP_t, RF_t, CL_t, FC_t, EN_t, RP_t) \quad (1)$$

Where AGR_t is agricultural value added as a proxy for agricultural output, CO_{2t} represents CO_2 emission, $TEMP_t$ indicates average rain temperature, RF_t indicates average rain temperature, CL_t indicates the land usage by kilometers by hectares, FC_t denotes fertilizers consumption, EN_t represents energy usage, and RP_t indicates rural population.

The above model was modified to suit the study variables in the Nigerian context with the inclusion of temperature anomalies, that is, an aggregation of average annual temperature and rainfall in Nigeria. Below is the modified model:

$$FPI_t = f(CO_2, TA_t, CL_t, FC_t, PO_t) \quad (2)$$

FPI_t is the food production index, which represents food security in Nigeria, CO_{2t} indicates Carbon dioxide emissions measures in metric tons per capita, and TA_t is temperature anomalies, which collectively represent the climate change variable in the model. CL_t is a proxy of land usage for agricultural production in Nigeria, FC_t represents fertilizer consumption at kilograms per hectare of arable land, and PO_t denotes the total population of the country. The study employs quarterly time series data covering the period 1991Q1–2023Q4 sourced from previous research [22,23].

3.2. Methods of Data Analysis

The study made use of machine learning regression algorithms due to the continuous numeric values of the study variables. Recent studies highlight the effectiveness of machine learning (ML) and IoT in improving agricultural systems under climate stress. Kassanuk and Phasinam show that ML can model non-linear interactions among variables like soil moisture, temperature, and humidity, outperforming traditional econometric methods [21]. Their work supports ML's role in precision irrigation, enhancing efficiency and climate adaptation. Algorithms such as SVM and K-NN improve decision-making by translating environmental data into actionable insights [24].

The adopted machine learning algorithms are multiple regressions, k-nearest neighbor (K-NN), random forest, and support vector machine classifiers. It is logical and pertinent to explore all available machine learning algorithms, starting from simple classifiers to complex ones, making assumptions to generalizations to attain the best-performing machine learning algorithm for prediction [25,26]. Nigeria's agriculture is greatly affected by climate variations, with differing rainfall and temperature patterns that produce non-linear impacts on productivity. This complexity is further influenced by ecological and socio-economic factors like land degradation, soil fertility, water availability, and rural-urban migration, which interact with climate variables. Studies show that the relationship between climate change and agricultural outcomes is not linear, as moderate temperature increases can benefit some crops, while extreme temperatures and irregular rainfall cause crop failures. Machine learning algorithms, such as Random Forest and Support Vector Regression, help model these non-linear interactions, better capturing the dynamic links between climate and food security. The details of the above-stated algorithms are as follows:

3.2.1. Regression models

The study applied various regression models to the dataset. The performance of the model can be evaluated by various metrics. Some of the metrics used for regression models are RMSE (Root Mean Squared Error), R-squared, and graphs. The mentioned performance measures are the most widely used metrics for comparing various models in machine learning regression analyses. The value of R-squared lies between 0 and 1. If the value is near 1, the model performance is good.

The equation for Machine Learning Regression is as follows:

$$Y_y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \mu \quad (3)$$

Here, Xi is an independent feature, β_0 is the y-intercept (constant term), $\beta_1 \ldots\ldots \beta_k$ are slope coefficients for dependent variables, μ is the model error term, and Y is a dependent variable.

3.2.2. K-Nearest Neighbour (K-NN) Algorithm

In statistics, the k-nearest neighbor algorithm (k-NN) is a non-parametric supervised learning method first developed by Evelyn Fix and Joseph Hodges in 1995, and later expanded by Thomas [27]. K-NN is called a lazy classifier, and it is one of the simplest ML Algorithms used for classification and regression. In both cases, the input consists of the K closest training examples in a dataset. The output depends on whether K-NN is used for classification or regression. When the algorithm is used for regression, as in the case of this study, a weight is assigned to the predicted and predictor values to enable a distance calculation between the predicted and actual values of the data point. The Euclidean distance is a good choice for such a distance function if the data is numerical. According to Idrizi et al. [28], K-NN model accuracy can be enhanced by normalization, particularly if the features represent different physical units or come in much different scales than normalizing because this algorithm relies on distance for classification. The following is the K-NN classifier:

$$\text{Euclidean Distance} = \sqrt{\sum_{k=1}^{p} (a_k - b_k)^2} \quad (4)$$

Equation 4 represents the K-NN classifier at Euclidean distance measurement parameter, where P is the number of dimensions, while a_k and b_k are respective attributes of in k-th component or data objects a and b. Every other distance measure parameter of the K-NN algorithm, such as Manhattan (MADM), Minkowski (MIDM), and Chebyshev (CHDM), is a normalized form of Euclidean distance (EUDM) mathematically.

3.2.3. Support Vector Machine

Support Vector Machine is a powerful algorithm that can handle both linear and non-linear classification problems. SVM can be particularly effective when there are many potential predictors and the relationship between the predictors and the outcome is complex. In the context of diagnosing dengue, SVM could be used to identify the most important symptoms and risk factors associated with the disease, and provide a more accurate diagnosis [29].

3.2.4. Random Forest Algorithms

Random Forest Regression is also called an ensemble classifier or algorithm. In the ensemble model, more than one ML model is used to predict the outcome. Random Forest uses several decision trees to predict the outcome. Thus, it is a powerful model and its predictive capacity surpasses other conventional machine learning algorithms.

4. Experimentation and Results

The collected time series data underwent data pre-processing by filling the missing values with the means of the particular column and outrightly removing any missing values of more than 50% as proposed by Olatunji [25]. This process helps to avoid bias in the data analysis. The study adopted a percentage data splitting of 70%–30% for training and testing, respectively.

4.1. Trend Analysis of Climate Change, Environmental Degradation, and Food Security in Nigeria (1991–2022)

The time series analysis in **Figure 1** provides a comprehensive view of the relationship between climate change, environmental degradation, and food security in Nigeria, spanning from 1991 to 2022. The analysis highlights the interactions between Temperature Anomalies (TA), representing climate change, CO_2 emissions, which indicate environmental degradation, and the Food Production Index (FPI), a key indicator of food security.

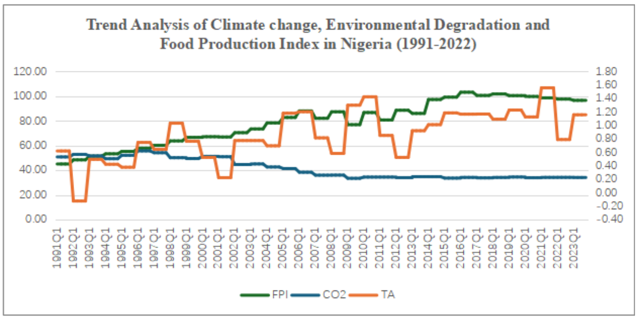

Figure 1. Trend Analysis of Climate Change, Environmental Degradation, and Food Production Index in Nigeria (1991–2022).

Temperature Anomalies (TA), shown in orange, reflect the deviations from long-term average temperatures over the years. The upward trend in temperature anomalies, particularly from the early 2000s onward, demonstrates a general warming of the climate, with periodic spikes indicating significant climatic stress events. These temperature anomalies are indicative of increasing temperatures in Nigeria, which can lead to heat stress, reduced crop yields, and disruptions in the growing seasons of essential crops. The upward trend in temperature anomalies aligns with a rise in agricultural challenges, especially for crops like maize, cassava, and rice, which are highly sensitive to temperature fluctuations. As temperature anomalies increase, the agricultural sector faces an escalating risk of crop failures and reduced food security, contributing to a decline in the FPI during these periods.

Similarly, CO_2 emissions (represented in blue) show a consistent rise over the years, reflecting the increasing environmental degradation in Nigeria. High CO_2 levels are primarily attributed to deforestation, industrial activities, and rapid urbanization. As CO_2 emissions increase, they exacerbate global warming and contribute to the greenhouse effect, which in turn affects rainfall patterns, soil fertility, and overall environmental health. CO_2 emissions are closely tied to land degradation and soil erosion, reducing the productive capacity of the land and further undermining agricultural productivity. The negative relationship between rising CO_2 emissions and food security is evident in the fluctuations of the Food Production Index (FPI), where higher emissions correspond to lower agricultural productivity.

The Food Production Index (FPI), represented by the grey line, tracks the overall agricultural productivity and food security in Nigeria. The FPI fluctuates over time, with notable declines in the early 1990s and early 2000s, which coincide with periods of heightened temperature anomalies and increasing CO_2 emissions. These declines reflect the negative impacts of both climate change and environmental degradation on Nigeria's agricultural sector. For example, the early 1990s saw a dip in FPI, possibly due to adverse climate conditions such as extreme heat, irregular rainfall, and soil degradation, which reduced crop yields and compromised food production. The increase in temperature anomalies and CO_2 emissions during these periods correlates with the reduction in agricultural output, which is captured in the drop in FPI values.

Despite some recovery and stabilization in the FPI from the mid-2000s onward, the overall trend suggests that agricultural productivity has not fully rebounded to the levels expected, considering the gradual improvements in agricultural practices and technologies. While there are instances of positive growth in the FPI, the general upward trend in temperature anomalies and CO_2 emissions continues to pose significant challenges. The interaction between temperature anomalies, CO_2 emissions, and the FPI indicates a complex relationship where climate change and environmental degradation act as persistent barriers to achieving long-term food security in Nigeria.

This trend analysis, presented in **Figure 1**, underscores the crucial role of climate change and environmental degradation in shaping food security in Nigeria. Rising temperature anomalies and increasing CO_2 emissions are directly linked to declining agricultural productivity as reflected in the FPI. This highlights the importance of addressing climate change and environmental degradation through sustainable agricultural practices, climate-resilient crops, and improved land management techniques. The ongoing upward trends in temperature and CO_2 emissions signal the urgent need for comprehensive climate adaptation strategies to safeguard Nigeria's food security in the coming decades.

4.2. Descriptive Analysis

The study made use of quarterly data of 132 samples from 1991 first quarter to the last quarter of 2023. The mean of the series is the average value of the variable over the period of study. Average values of FPI, CO_2, TA, FC, and POP are 45 on a constant value of 100 from (2014–2016),0.36 metric tons per capita, 0.85 degrees Celsius, 73.882 per hectare of arable land, 12.774 per hectare and 18.805 total head counts per annual in Nigeria.

The maximum is statistically the highest value of the series for the period under study. **Table 1** shows that maximum values for FPI, $C0_2$, TA, CL, FC and POP are 103.29 on a constant value of 100 from (2014–2016), 0.62 metric tons per capita, 1.56 degree Celsius, 76.79 per hectare of arable land, 45.44 fertilizer consumed per hectare and 19.216 Nigerians per annual. The minimum is statistically referred to as the lowest value of the given series of studies. **Table 1** indicates that the minimum values of the mentioned variables accordingly are 45 food production index, 0.22 metric tons per capita, −012 degrees Celsius, 70.19 per hectare of arable land, 4.15 fertilizer consumption per hectare, and 18.397 Nigerians per year within the study scope.

Table 1. Descriptive Statistics.

	CO_2	TA	CL	FC	Log(POP)	FPI
Minimum	0.22	−0.12	70.19	4.15	18.397	45
Maximum	0.62	1.56	76.79	45.44	19.216	103.29
Mean	0.36	0.859	73.882	12.774	18.805	79.274
Std. Dev.	0.146	0.363	1.787	10.82	0.247	17.718
Observation	132	132	132	132	132	132

Source: Author's Compilations using WEKA (2024).

Keynotes: FPI = Food production index proxy food security in Nigeria, CO_2 = Carbon dioxide emissions (metric tons per capita), TA = Temperature Anomalies, CL = Land usage for agricultural production Nigeria measures by arable land per hectare, FC = Fertilizer consumption per hectare and POP = Logarithm of total annual head counts in millions.

Standard deviation is a measure of dispersion in a series of studies. **Table 1** reveals the dispersion levels of each variable from their various mean as follows: FPI is 17.718, CO_2 emission is 0.146 metric tons per capita, TA is 0.36 degrees Celsius, CL is 1.787, FC is 10.82, and POP is 0.247, respectively. Climate change factors of carbon dioxide emission, temperature anomalies, and total population have the largest spread among other variables of the study, while arable land for production and food production index and fertilizer consumption per hectare have the lowest spread among the variables of the study.

Table 2 shows the correlation relationship and impact between the predictor variables and the predicted variable. **Table 2** reveals that carbon dioxide emission (CO_2), a proxy for environmental degradation, has a negative relationship with the food production index, a food security indicator in Nigeria, within the study period. Every other predictor variable, apart from $CO_{2,}$ has a significant positive relationship and impact on the predicted variable of food security in Nigeria within the study scope. This is an insight into the variables' deterministic strength with the predicted variables, a critical process in machine learning feature engineering for optimal outputs. Hyperparameters were tuned for several algorithms to optimize the model's performance. For K-Nearest Neighbors (K-NN), the value of K (the number of nearest neighbors) and the distance measure (Euclidean) were adjusted. The value of K was selected through cross-validation to ensure the model was neither too simplistic nor overfitted. In the case of Support Vector Regression (SVR), the C parameter (penalty parameter) was optimized, and a polynomial kernel was chosen to achieve the best fit for these data. The C value controls the trade-off between minimizing error on the training data and reducing model complexity. For the Random Forest (RF) model, parameters such as the number of trees (Executive Number) and the random seed were tuned to ensure reproducibility while balancing computational efficiency and model performance. These hyperparameters were selected through an iterative process of testing various values and evaluating performance using metrics like R-squared, RMSE, and cross-validation results.

Table 2. Correlation Analysis.

Predictor Variables	Correlation with Predicted Variable
CL	0.9644
POP	0.9353

Table 2. *Cont.*

Predictor Variables	Correlation with Predicted Variable
TA	0.7181
FC	0.4809
CO_2	−0.9119

Source: Author's Compilations using WEKA (2024).

Table 3 shows hyperparameter tuning of the various selected machine learning algorithms for optimal results. K-nearest neighbour (K-NN) is a classification algorithm that is also applicable in machine learning and regression analysis. The main parameters tuned in K-NN were its nearest neighbour closet value (K) and distance measures. The K value that gave the optimal result of the K-NN algorithms in this study is K = 3, and the distance measure chosen for this study is Euclidean. The multiple linear machine learning regression model selected for this study operated on the default mode of all the parameters in the Weka environment. **Table 3** also reveals that Support vector regression (SVR) and random forest (RF) hyperparameter optimization were conducted on various parameter values such as: SVR (C = 2, Kernel = poly kernel), RF (Executive Number = 1, Seed = 2). The listed hyperparameter tuning values gave the optimal results of the various algorithms selected for this study.

Table 3. Optimization Strategies.

Algorithm	Parameter	Value
Multiple Regression Model (MRM)	All Parameters	At Default
K=Nearest Neighbour (K-NN)	K	3
	Distance Measure	Euclidean
Support Vector Regression (SVR)	C	2
	Kernel	Polykernel
Random Forest (RF)	Executive Number	1
	Seed	2

Source: Author's Compilations using WEKA (2024).

4.3. Regression Analysis

The study employed a machine learning regression algorithm to analyze the food security series and its determinants. The optimal results obtained from this analysis are presented in **Table 4.**

Table 4. Comparison of the Selected Machine Learning Regression Models.

ML Models	R-Square	Root Mean Square Error (RMSE)
Multiple Linear Regression (MLR)	0.9622	16.7232
K=Nearest Neighbour (K-NN)	0.9934	2.1414
Support Vector Regression (SVR)	0.9761	4.124
Random Forest Regression (RF)	0.9731	9.3908

Source: Author's Compilations using WEKA (2024).

Table 4 presents the results of the machine learning regression algorithms used in this study. The performance of these algorithms is assessed using key machine learning evaluation metrics, including R-Square (which measures the proportion of the variance in the predicted variable explained by the predictor variables), Mean Absolute Error (MAE) (the average of the absolute differences between predicted and actual values), and Root Mean Squared Error (RMSE) (the square root of the mean squared error, which provides an error metric in the same units as the original data). Ideally, the chosen model should exhibit a high R-squared and a minimal Root Mean Squared Error (RMSE) compared to other models. According to Table 4 and Figure 1, the K-Nearest Neighbor (K-NN) algorithm yields the highest R-Square value of 0.9934 (approximately 99%) and the lowest RMSE of 2.1414, outperforming the other selected algorithms in the study.

4.4. Graphical Evaluation Metrics of the Selected Algorithms

The graphical evaluation metrics of the models provide a visual confirmation of the performance of the selected regression algorithms, based on the alignment between the actual and predicted values. These graphs offer a comparison of how well the regression lines fit the data, further validating the model's performance. The following graphical comparisons illustrate the results of the various machine learning regression algorithms used in this study (**Figures 2–5**).

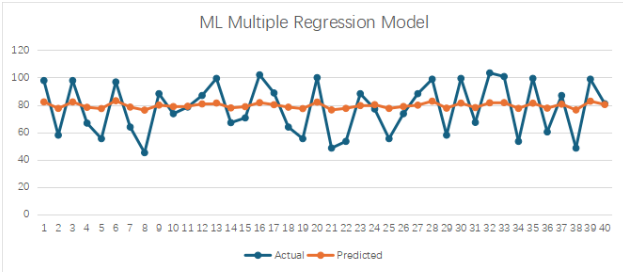

Figure 2. ML Multiple Regression Model.

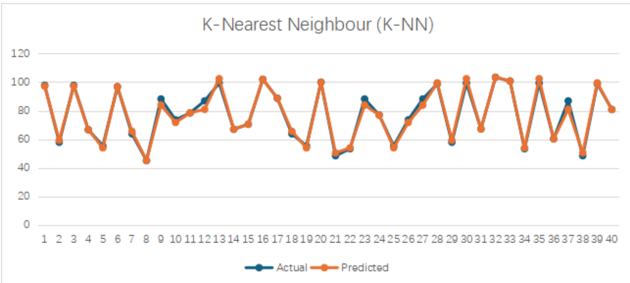

Figure 3. K-Nearest Neighbour (K-NN).

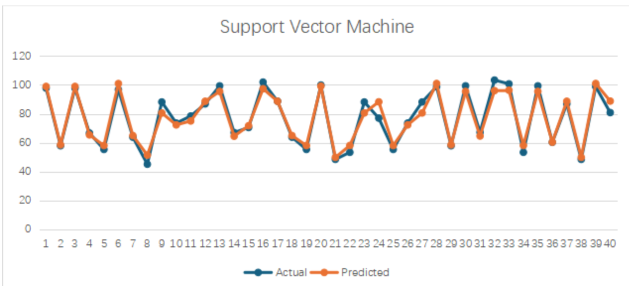

Figure 4. Support Vector Machine.

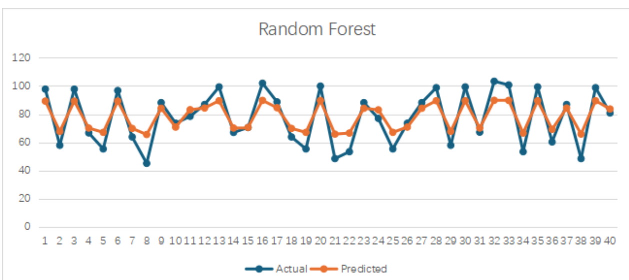

Figure 5. Random Forest.

The graphical performance evaluation clearly shows that the K-Nearest Neighbor (K-NN) model exhibits well-fitted regression lines between the actual and predicted values. This visual confirmation further supports the superiority of the K-NN algorithm, demonstrating it as the best-performing model among those selected for the study.

4.5. Discussion of Findings

The results of this study provide key insights into the impacts of climate change and environmental degradation on food security in Nigeria. The findings show that CO_2 emissions, which proxy environmental degradation and temperature anomalies representing climate change significantly, reduce food production, consistent with previous research. The negative relationship between CO_2 emissions and the food production index (FPI) aligns with Gobezie and Boka [4], who also found that higher emissions increase malnutrition and reduce food security in Sub-Saharan Africa. In this study, CO_2 emerged as a critical predictor with a strong inverse correlation, supporting the literature on its adverse impact on agricultural output.

Similarly, the positive link between land use (CL) and food security is supported by the finding of [1], who noted that reversing land degradation can boost production. The findings highlight the importance of sustainable land management practices, echoing the recommendations of Okoli, M.I. and Ifeakor for adopting efficient farming methods to mitigate climate effects [3]. Temperature anomalies (TA) showed a strong negative correlation with food production, aligning with the work [6], who noted that rising temperatures in Sub-Saharan Africa harm crop yields. This also supports Ajetomobi et al. [10], who projected a 30% decline in Nigerian agriculture by 2050 due to climate change, highlighting the vulnerability of staple crops like maize and cassava.

Fertilizer consumption (FC) had a positive but weaker influence on food production, reinforcing Alhassan et al. who noted that while fertilizer helps, its benefits are limited without other adaptive strategies like improved technology and education [2]. Finally, the use of machine learning models, including K-Nearest Neighbour (K-NN) and Random Forest, proved highly effective, with K-NN achieving an R-squared of 0.9934. This aligns with findings of Olatunji [25], who recommend machine learning for uncovering complex relationships and aiding policymakers in enhancing food security through data-driven insights.

The results from the study indicate that climate variables, particularly CO_2 emissions and temperature anomalies, significantly affect agricultural productivity and food security in Nigeria. As observed, temperature anomalies, which represent deviations from average temperatures, hurt crop yields, particularly for maize, cassava, and rice. These crops are highly sensitive to temperature fluctuations, with extreme heat and temperature variations leading to heat stress and reduced yields [10]. Studies have shown that rising temperatures in Sub-Saharan Africa are detrimental to crop yields, contributing to a 30% decline in agricultural production by 2050. Similarly, increasing CO_2 emissions exacerbate the greenhouse effect, leading to global warming, which disrupts rainfall patterns, soil fertility, and overall agricultural productivity. In particular, deforestation and industrial emissions are linked to soil degradation, further decreasing land productivity and affecting crop growth.

The findings also highlight how temperature anomalies and CO_2 emissions influence food production through their combined effects on environmental conditions such as soil fertility and rainfall distribution. For example, the negative impact of temperature anomalies on crop growth, especially for cassava and maize, underscores the need for climate-resilient agricultural practices to mitigate temperature stress. Land use and fertilizer consumption also play a role in food production, where fertilizer consumption can support crop growth, but its benefits are limited when combined with unsustainable land management practices and the ongoing environmental degradation caused by rising CO_2 emissions.

5. Conclusions

This study highlights the significant impacts of climate change and environmental degradation on food security in Nigeria. Key climatic factors, such as CO_2 emissions, temperature anomalies, and unsustainable land use, have been shown to negatively affect agricultural productivity, thereby threatening food security. The analysis emphasizes the urgent need for adaptive strategies to mitigate these adverse effects. Sustainable land management practices, along with climate-resilient agricultural methods, can alleviate some of the negative consequences of climate variability on food production. Additionally, fostering innovation in agricultural technologies and improving access to resources for smallholder farmers is crucial to enhancing their resilience to climate shocks.

The machine learning techniques employed in this study provide a more detailed examination of the relationships between climate variables and food security, offering insights beyond simplified, linear models. By leveraging machine learning models, such as K-Nearest Neighbours (K-NN) and Random Forest, the study reveals these non-linear relationships more effectively than traditional econometric models, providing a clearer, data-driven framework for climate adaptation strategies. These predictions can guide agricultural policy and practice, promoting more climate-smart agriculture and improving resilience to climate shocks.While the study is limited by the exclusion of broader socioeconomic factors such as economic policies, migration, political stability, and market access, which are critical to food security, it prioritizes a climate-centric perspective to provide a clearer understanding of the direct impact of climate change on food security. Future research could incorporate these factors for a more comprehensive analysis.

Author Contributions

Conceptualization, K.S.A. and H.S.; methodology, H.S.; software, H.S.; validation, K.S.A., H.S., and K.D.O.; formal analysis, K.S.A.; resources, K.D.O.; data curation, H.S.; writing—original draft preparation, K.S.A.; writing—review and editing, H.S. and K.D.O.; visualization, H.S.; supervision, K.S.A.; project administration, K.D.O. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the results of this study can be found in the publicly available datasets from the sources [22,23].

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Conflicts of Interest

The authors declare no conflict of interest.

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