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The impact of climate change on aquaculture and fisheries production in Nigeria

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ABSTRACT

Nigeria fisheries and aquaculture industries are under much pressure from climate change. The Sustainable Development Goals (SDGs) of poverty alleviation, eliminating hunger, excellent health and well-being, tackling climate change, and life below the ocean are all in grave danger of being missed by Nigeria. Hence, the study examined the impact of climate change on aquaculture and fisheries production in Nigeria. Data used was gathered from FAOSTAT, Statista, and the World Development Indicators databases from 2009 – 2022, including aquaculture productivity, temperature, rainfall, and CO₂. Descriptive statistics, Granger causality, panel unit root, correlation test, and Fully Modified Least Squares (FMOLS) were employed to analyze the data. The result of descriptive statistics shows that no outliers among the variables. VIF demonstrates that the variables are not collinear. The unit root of stationarity utilizing PP and ADF methods shows that the variables have a mixed order of level I(0) and a first difference order integration I(1). FMOLS estimated results show that rainfall (-0.694) was statistically significant at the 5% level. CO₂ (1.778) was statistically significant at the 1% level. Correlation reveals a strong relationship between CO₂ (0.903) and aquaculture productivity. CUSUM and CUSUMSQ tests demonstrate the stability of the values at 5%. As the Granger causality test shows, all variables are susceptible to short-run causation. The study consequently recommends severe rules to prohibit intensive aquaculture in areas with significant CO₂ sequestration; apply effective adaptation strategies; improve management processes; and invest in climate-resilient systems.

Keywords: Aquaculture, CO₂, climate change, FMOLS, rainfall, temperature

1. INTRODUCTION

Physical, environmental, social, and economic stressors already present in the African coastal zone are made worse by climate change. Additionally, it presents serious, long-term dangers to fisheries in many tropical developing nations, particularly Sub-Saharan Africa (SSA). Fisheries and the effectiveness of their management have always been impacted by natural climate oscillations, especially those occurring on a medium (decadal) scale (Garcia and Rosenberg, 2010). Over the next 50 to 100 years,

the ocean and atmosphere will continue to warm, sea levels will rise due to glacier melting and thermal expansion, and the pH of the sea will drop (becoming more acidic) as more carbon dioxide is absorbed (Griggs and Reguero, 2021).

Circulation patterns may alter locally, regionally, and globally. The variety of habitats and particular species they sustain determine how each species reacts to the many effects of climate change. The impact of the changing climate on fisheries worldwide cannot be generalized, but they have one thing in common: changes in fish populations are very particular to result from climate change. Many disadvantaged communities and national economies that rely extensively on fisheries could face severe economic effects due to variability in fish populations (Brander, 2010).

The global environment and economies are being threatened by climate change, which has severe ramifications for aquaculture and fisheries. The consequences of climate change are becoming more noticeable in Nigeria, a nation with long coasts and a rich fishing heritage (Okon et al., 2021). Millions of people in Nigeria depend on the fishing industry for their living, and it also makes a substantial contribution to the country's protein intake (Odioko and Becer, 2022). However, fish habitats are shifting, and rising temperatures, altered precipitation patterns, and a rise in the incidence of severe weather are disrupting aquatic ecosystems. These modifications put the sustainability of these essential resources in jeopardy, affecting both systems of aquaculture and wild catch fishing operations.

Changes in fish species distribution have been connected to rising sea temperatures, which may impact regional fishing methods and biodiversity (Nuon et al., 2024). Climate change-related increases in drought and flood frequency and severity worsen aquaculture systems' vulnerability by affecting fish health and water quality. Moreover, the health of aquatic animals is threatened by ocean acidification, another effect of climate change, especially for species with calcium carbonate components.

According to research, the Nigerian aquaculture and fisheries industry is facing a variety of effects from climate change that need flexible management techniques. Research has indicated a reduction in fish populations and alterations in the species makeup, thereby jeopardizing the financial sustainability and food supply in communities that depend on these resources (Ndong et al., 2015). Both the accessibility and value of water, which are critical for maintaining fish health and output, complicate aquaculture activities (Ezeh et al., 2020).

In general, there is an increasing acknowledgement that climate change threatens the sustainability of fisheries and aqua farming. Nigeria, a country that relies heavily on aquatic resources for food, money, and revenue generation, is particularly concerned about the consequences of climate change. The key problem is how climate change impacts fisheries and aquaculture, putting the industry's profitability, as well as the status of both the environment and the economy, at risk. This research establishes the groundwork for future studies on the effects of climate change on Nigerian fisheries and aquaculture industries. Achievement of the Sustainable Development Goals (SDGs) of eliminating poverty, eradicating hunger, achieving outstanding health and well-being, combating climate change, and conserving life below the ocean is essential to Nigerian sustainability. This study used yearly time-series data collection from 2009 to 2022 to explore the impacts of climate change on Nigerian fisheries and aquaculture productivity.

2. LITERATURE REVIEW

2.1 The Earth Climate System and Aquaculture

Climate refers to the long-term weather variable of a region. The troposphere, lithosphere, stratosphere, biosphere, and cryosphere all interact to determine the Earth's climate. As a result, the climatic structure incorporates the passage of both energy and moisture between these spheres.

The oceans generally govern the global climate. Due to their significantly higher heat capacity (as well as gross energy uptake) than the atmosphere (Griggs and Reguero, 2021), they can absorb a sizable portion of the world's heat emissions. The dynamics of the region's aquatic habitats may alter as a result of these temperature variations in the ocean. Fish landings may decrease due to modified ocean dynamics, particularly in coastal fisheries, which may also affect fish migration patterns. Biodiversity is also threatened by rising water temperatures. Fish often have a predilection for heat that maximizes physiological functions (Abowei, 2010).

A species' survival is in jeopardy if the water temperature goes over its upper limit of tolerance. Since there are no fish in most of the Bangwa Rivers, women in the Lebialem Highlands of Cameroon have taken to hunting tadpoles and frogs (Taboue et al., 2023). However, even the frog and tadpole populations have drastically decreased (in part) due to warmer rivers that have brought more predator fish into formerly uninhabited areas. The following is a summary of the main concerns about how fish output is impacted by climate change:

Changes in aquatic ecosystems and the distribution of species:

Rising sea temperatures, changed precipitation trends, and an increase in the likelihood of hazardous weather occurrences are all results of climate change. The distribution of fish species is shifting due to these changes to aquatic ecosystems, which may also interfere with conventional fishing methods. Fish populations and biodiversity are reduced as a result, which may threaten local economies that depend on the aquaculture and fishing sectors (Ndong et al., 2015).

Decreased aquaculture output:

Aquaculture accounts for a larger component of Nigerian seafood supply and is particularly vulnerable to variations in both quantity and quality of water caused by climate change. Increasing water temperatures and extreme weather events such as flooding and drought can have a detrimental effect on aquaculture systems by reducing fish growth rates, increasing fish mortality, and degrading water quality (Ezeh et al., 2020). This decline in productivity may have an impact on the financial stability and food supply of fish farmers.

Ocean acidification:

Ocean acidification is a direct result of growing CO₂ levels in the atmosphere, and it poses a significant threat to aquatic life. Species having calcium-carbonate building components, such as shellfish, are especially vulnerable. Nigeria's fisheries may be further impacted by the influence of ocean acidification on fish and other aquatic creatures, which may result in lower fishing yields and changed marine ecological systems (Griggs and Reguero, 2021; Ezenwa, 2022).

Social and economic ramifications:

There are significant financial and societal ramifications when declining fish supplies, lower aquaculture production, and changing ecosystems come together. These include increased food prices, reduced revenue for fishing settlements, and potential conflicts over limited resources. Because of their vulnerability, these communities require adaptable policies and management strategies to mitigate the detrimental effects of climate change (Ezenwa, 2022).

To summarise, there are several sides to the question of how climate change is affecting Nigeria fisheries and aquaculture, including ecological disruptions, diminishing productivity, economic issues, and social consequences. To address these issues, a detailed understanding of how aquatic systems and climate change interact is required, as well as the development of adaptive strategies to ensure the long-term survival of Nigeria aquaculture and fishing businesses.

2.2 Theoretical Framework

This study focused specifically on the Milankovitch theory. The periodic fluctuations in Earth orbit and axial tilt that impact the planet climate over extended periods are described by Milankovitch theories, which are named after the Serbian mathematician and astronomer Milutin Milankovitch (Caccamo and Magazu, 2021). These ideas are essential for comprehending how the climate naturally changes over tens to hundreds of thousands of years. Here is a quick summary of the cycles of Milankovitch and how they affect climate. Next, we look at how the productivity of fisheries and aquaculture is affected by climate change as a result of both natural and artificial variables. Milankovitch recognized three principal cycles that impact the climate of Earth. These cycles include:

Eccentricity:

This is the form of Earth's orbit around the Sun, which changes over 100,000 years from almost circular to slightly elliptical. The quantity of solar energy that reaches the Earth varies with variations in eccentricity.

Axial Tilt (Obliquity):

Over a cycle of around 41,000 years, the angle of Earth's axial tilt swings between 22.1 and 24.5 degrees, resulting in numerous extraordinary events occurring, including changes in the seasons across the world. The severity of the season is influenced by this tilt.

Precession:

This is the Earth's rotational axis wobble, which shifts the axial tilt direction over 26,000 years. The timing of the seasons of Earth's orbit around the Sun is impacted by precession.

These cycles are expected to influence long-term climate trends by altering the precise timing of glacial and interglacial eras.

2.3. Climate change impact on fisheries and aquaculture production

1. Temperature changes: Rising global temperatures are caused by greenhouse gas emissions. This warming affects fisheries and aquaculture in numerous ways:

- i. **Species distribution:** Several species of fish are migrating to cooler waters. This shift can potentially have a severe influence on present aquaculture and fishing operations, particularly in locations where particular species are important commercially or culturally.
- ii. **Reproduction and growth rates:** Warmer temperatures can influence the growth of aquatic organisms, reproduction, and overall survival. Warmer waters, for example, can cause particular species to develop more quickly, but they can also lower the oxygen content of the water, which can harm aquatic life (Hochachka and Somero, 2002).
- iii. **Disease and parasites:** In the aquaculture sector, higher temperatures can potentially raise the frequency of parasites and diseases. Infections can more easily affect stressed fish due to increased temperatures (Harvell et al., 1999).

2. Acidification of the ocean: Ocean acidification is caused by rising carbon dioxide (CO₂) levels, and it has an impact on aquatic ecosystems:

- i. **Structures of calcium carbonate:** Mollusks and corals are species that cannot produce their skeletons and outer shells due to acidification. On marine food webs, this may have cascade impacts (Orr et al., 2005).
- ii. **Behavior of fish:** According to specific research, fish migratory patterns and interactions between predators and prey may be impacted by acidification (Munday et al., 2009).

3. Variations in sea levels and ocean currents: Sea levels have risen by approximately 10–20 cm worldwide during the twentieth century, mainly due to thermal expansion. Based on the full range of 35, the Intergovernmental Panel on Climate Change provides climate forecast scenarios (Organization for Economic Cooperation and Development, OECD, 2011), a worldwide increase in sea levels of 9–88 cm is anticipated by 2100:

- i. **Ocean currents:** Changes in currents in the ocean can affect aquatic life migration patterns and nutrient distributions. The accessibility of resources for aquaculture and wild fisheries can be impacted by current changes (Burrows et al., 2014).
- ii. **Sea levels:** Coastal fish farming equipment, especially that located in relatively low-lying locations, may be impacted by the increasing sea levels. Increased floods and intrusion of salt can affect the aquaculture output and well-being (Nicholls and Cazenave, 2010).

3. METHODOLOGY**3.1 Study Design**

Nigeria is a country in West Africa within Sub-Saharan Africa. Nigeria is in the tropics, with a land area of approximately 923,768 km² and 850 km long coastline (Allu and Ochedi, 2015). Nigeria is around 1100 km long from north to south and 1300 km wide from east to west (Aroyehun et al., 2023). This, however, explains the differences in Nigeria's climate and the extent to which different regions of the country are affected by climate fluctuation.

The panel data utilized in this research spans the years 2009 to 2022 and includes the following: aquaculture production (measured in metric tons [MT]), temperature (measured in degrees Celsius [°C]), rainfall (measured in millimeters [mm]), and carbon dioxide emissions (measured in kiloton [kt]). The data were obtained from Statista, FAOSTAT, and the World Development Indicators.

3.2 Analysis Estimation

3.2.1 Technique of Estimation

The estimated approach describes the methodologies for data analysis, statistical criteria, variable stationary patterns tests, theoretically justified a priori expectations, the dynamical model structure, and data sources of information. In addition, logarithms of the variables were computed to match the time series data.

3.2.2 Statistical Criteria

In this work, a set of statistical criteria was used to assess the statistical reliability of the calculated values. The multiple determination coefficient (R^2) and adjusted R-squared are necessary parameters. -Durbin-Watson statistics, long-run variance, and T- and F-statistics.

3.2.3 Economic A priori Expectations

If the signs of each explanatory variable in the model are compatible with a postulate of economic theory, then the a priori expectations should show that each explanatory variable in the model is comparable to that postulate. It is anticipated that rising temperatures will have a detrimental impact on fisheries and aquaculture productivity, while rising precipitation will have a mixed effect. If we estimate the model utilising the Fully Modified Least Squares approach, the coefficients should look like this (Table 1):

Table 1. Coefficient Expected sign

Coefficient (LnAquapro)	Expected sign
LnTemp	-
LnRainfall	+/-
LnCO2	-

3.2.4 Model Specification

The fundamental model considers precipitation, temperature, and CO₂ to predict fishery and aquaculture production. The model's implicit form may be expressed as follows:

$$\text{Aquapro} = f(\text{Temp}, \text{Rainfall}, \text{CO}_2) \quad (1)$$

The model assumes a non-linear shape, which is also articulated explicitly as follows, as used by Zhuang et al., (2022) and Olaifa et al., (2022).

$$\text{Aquapro}_{i,t} = f(\beta_0, \text{Temp}_{i,t}^{\beta_1}, \text{Rainfall}_{i,t}^{\beta_2}, \text{CO2}_{i,t}^{\beta_3}) \quad (2)$$

Where,

Aquapro = Aquaculture and fisheries production

Temp = Temperature

Rainfall = Rainfall

CO₂ = Carbon dioxide emissions

i = Figure of cross-sections

t = time in years

Equation (2) may be translated into the double-log model, expressed thus:

$$\text{LnAquapro}_{i,t} = \beta_0 + \beta_1 \text{LnTemp}_{i,t} + \beta_2 \text{LnRainfall}_{i,t} + \beta_3 \text{LnCO2}_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where,

Ln = Natural logarithms

ε = error term

The Fully Modified Ordinary Least Squares (FMOLS) estimator, used by Pedroni (2000) and Olaifa et al., (2022), is stated as follows:

$$\hat{\beta}_{FMOLS} = (\sum_{t=1}^T X_t' P_t X_t)^{-1} (\sum_{t=1}^T X_t' P_t Y_t) \quad (4)$$

Where;

$\hat{\beta}_{FMOLS}$ = Vector of estimated coefficients using the FMOLS estimator.

X_t = Matrix of independent variables for period t
 P_t = Matrix of weighting coefficients for time t to address serial correlation.
 Y_t = Vector of dependent variable(s) for time period t .
 t = Number of periods in the panel data.

The Granger causality test, as used by Wang et al., (2022) and adopted, is estimated as follows;

$$X_t = \alpha_o + \sum_{j=1}^k \alpha 1sXt - s + \sum_{j=1}^k \alpha 2sXt - m + \varepsilon_{1t} \tag{5}$$

$$Y_t = \beta_o + \sum_{j=1}^k \beta 1sXt - j + \sum_{j=1}^k \beta 2sXt - h + \varepsilon_{1t} \tag{6}$$

Equations (5) and (6) suggest no relationship between 1t and 2t. Granger causes in X should be Y Granger if the estimated coefficient $\alpha 2i$ is sufficiently significant (≤ 0). $\beta 2h$ is considered statistically significant only if the relationship between the two variables is greater than zero, such as when $c2h \neq 0$. Two separate variables are connected, indicated by the significance of the parameters 2i and 2h. If $\beta 2h$ and $\alpha 2i$ both equal zero, the Y and X parameters become autonomous. The data was analyzed using Gretl, SPSS, and Eviews 10.0.

4. RESULT AND DISCUSSION

4.1 Stationarity Test

When the mean, variance, and covariance of a time series are constant regardless of the measurement location, the data is said to be stationary. Nonetheless, a time series is not stationary, irrespective of the point at which it is observed, if its mean, variance, and autocovariance are not equal. This is a unit root issue. This indicates that just the period under consideration is suitable for the behavior analysis of that time series. Because non-stationary series might provide erroneous regression results when regressed on one another, the test is essential in determining if the time series is stationary over the long term. For this reason, the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) stationary tests were used in this study.

Table 2: Stationarity of unit root test

Variables	Unit root test for ADF		Unit root test for PP	
	Level	First difference	Level	First difference
LAquapro	5.303***	6.902***	4.553***	7.644***
	[0.001]	[0.000]	[0.004]	[0.000]
LTemp	3.063*	4.568***	2.941*	6.526***
	[0.055]	[0.005]	[0.068]	[0.000]
LRainfall	4.110***	8.462***	4.075**	8.836***
	[0.000]	[0.000]	[0.010]	[0.000]
LCO2	3.535**	5.075***	7.111***	4.617***
	[0.025]	[0.000]	[0.000]	[0.005]

ADF stands for Augmented Dickey-Fuller; PP is for Phillips-Perron; significant levels are indicated by ***, **, and *, at the 1%, 5%, and 10% levels, respectively.

Table 2 shows the outcomes of the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit root result tests, every variable was stationary at first difference. The statistical test values for the ADF and PP tests must be larger than the critical value at the 5 percent absolute term, following the requirements for the ADF and PP unit root tests, to demonstrate stationarity at the level. The same standard is used for differencing if it is not. Consequently, the stationarity of the unit root test findings shows a mixed order of integration at level I(0) and first difference order I(1).

Furthermore, Table 3 demonstrates the absence of multicollinearity, which indicates the absence of multicollinearity among the variables. The models were accurate and suitable for measuring the collected data as the Variance Inflation Factors (VIF) values were more significant than one (1) and also fell within the permitted range, and the Tolerance level (nearly equal to one [1]).

Table 3: Collinearity diagnosis

Variables	Collinearity Statistics	
	Tolerance	Variance Inflation Factors (VIF)
Temperature	0.748	1.336
Rainfall	0.959	1.042
CO2	0.728	1.374

4.2 Descriptive Statistics

Descriptive statistics were employed to provide a clear image of the quantitative description of a collection of data's fundamental characteristics. The mean, median, and mode are engaged in the research to indicate tendency; standard deviation and variance are used to measure variability; minimum and maximum levels are measured; and Kurtosis and Skewness are measured.

Table 4: Summary of descriptive statistics

Variables	AQUAPRO (MT)	TEMP (°C)	RAINFALL (mm)	CO2 (kt)
Mean	265521.9	27.50714	1179.294	105086.6
Median	277175.5	27.47500	1199.830	108299.0
Maximum	316727.0	27.86000	1296.780	119544.1
Minimum	152796.0	27.15000	1051.710	76947.40
Std. Dev.	46534.42	0.206115	80.94876	11721.84
Skewness	-1.124929	0.164770	-0.346105	-1.073690
Kurtosis	3.530818	2.153657	1.759880	3.363087
Jarque-Bera	3.117114	0.481188	1.176614	2.766794
Probability	0.210439	0.786161	0.555267	0.250725
Sum	3717306.	385.1000	16510.12	1471212.
Sum Sq. Dev.	2.82E+10	0.552286	85185.12	1.79E+09
Observations	14	14	14	14

Table 4 illustrates the highest aquaculture production of 316727MT and the minimum value of 152796MT, with a mean value of 265521.9MT and a standard deviation of 46534.42MT. In addition, the temperature was estimated to have an average value of 27.51 °C, with a standard deviation of 0.21 °C, a low value of 27.15 °C, and a maximum value of 27.86 °C. Likewise, Nigeria was expected to get 1296.78 mm of rainfall at its peak, 1051.71 mm at its lowest, and 1179.29 °C at its average, with an 80.95 mm standard deviation. With a minimum of 76947.4 kt, a mean of 105086.6 kt, and a standard deviation of 11721.84 kt, the maximum CO2 value was 119544.1 kt.

Normality test was examined using skewness and Kurtosis. Skewness is a measure of asymmetry and deviation from the normal distribution (Thadewald and Büning, 2007). The temperature time series skewness was more credible than zero, meaning that the variable concentration is to the left of its mean, displaying extreme values on the right. The variables for CO2, rainfall, and aquaculture production, on the other hand, were negatively skewed to the left, suggesting that the variable is concentrated on the right side of its mean, demonstrating an extreme left side. Additionally, Kurtosis is another indication in distribution analysis that is used to denote flattening or peakedness.

The Jarque-Bera (JB) test measures how well the sample data follows an acceptable distribution pattern with regarding skewness and kurtosis (Jarque and Bera, 1980). Therefore, to evaluate departures from normalcy, the JB test combines skewness and kurtosis measurements. The JB test was used to check if the residuals were normal (Thadewald and Büning, 2007). In other words, the residuals are regularly distributed if the JB test yields a p-value larger than 0.05. This value indicates that the residuals had a normal distribution, given that the p-value of the JB test for normality for every investigation model was above 0.05. As a result, the considerable p-value suggests no discernible departure from normalcy in the data.

4.3 Pairwise correlation tests

A pairwise correlation test assesses the path and magnitude of an association involving two variables. The correlation coefficient value, which ranges from -1 to 1, reflects the relationship path and magnitude.

Table 5: Pairwise correlation test

Variables	LAQUAPRO	LTEMP	LRAINFALL	LCO2
LAQUAPRO	1			
LTEMP	-0.374	1		
LRAINFALL	-0.037	-0.106	1	
LCO2	0.903	-0.499	0.169	1

Table 5 shows the pairwise correlation. There is a strong positive correlation (0.903) between CO₂ emissions (LCO₂) and aquaculture production (LAQUAPRO). This suggests that LCO₂ grows considerably along with an increase in LAQUAPRO. However, there is a negative correlation (-0.374) between temperature (LTEMP) and aquaculture productivity (LAQUAPRO). This suggests that LAQUAPRO rises when LTEMP decreases. Additionally, there is a small negative association (-0.037) between rainfall (LRAINFALL) and aquaculture production (LAQUAPRO). This suggests that at a given LRAINFALL, LAQUAPRO will be at its apex. LTEMP and LRAINFALL have an extremely low negative correlation (-0.106), indicating a feeble linear association. The moderately negative association between LTEMP and LCO₂ (-0.499) shows that higher temperatures may be associated with lower LCO₂ levels; that is, when LTEMP rises, LCO₂ tends to fall somewhat. LRAINFALL and LCO₂ have a modest positive connection (0.169), suggesting a minor propensity for both variables to rise in tandem. As expected, there is a negative association between LRAINFALL and LTEMP, and LAQUAPRO.

4.4 Results of Fully Modified Ordinary Least Squares (FMOLS)

Table 6: Estimated Panel Fully Modified Least Squares (FMOLS)

Variables	Coefficient	Standard error	T-statistic	p-value
CONSTANT	-15.914	12.646	-1.259	0.240
LTEMP	3.845	3.282	1.172	0.274
LRAINFALL	-0.694**	0.314	-2.211	0.050
LCO ₂	1.778***	0.289	6.153	0.000
R-squared (R ²)	0.648	Adjusted R-squared		0.531
Long-run variance	0.006	Durbin-Watson		1.95

Significant at 1%, 5%, and 10% are indicated by ***, **, and * respectively.

A practical method for characterizing long-run adjustment processes is Fully Modified Ordinary Least Squares (FMOLS). Multiple time series models, or FMOLS models, are used to assess the problem of independent variable correction in time series data (Olaifa et al., 2022). FMOLS is the Co-integrating Equation Model (Olaifa et al., 2022). The long-term influence of the independent factors on the dependent variable was ascertained using the FMOLS estimating method.

Table 6 displays the FMOLS results for which the R-squared (R²) value of 0.648 was obtained. This value suggests that the independent variables in the model account for nearly 64.8% of the variation in the dependent variable. This indicates that the data matches the model effectively. R-squared adjusted (0.531); this modifies the R² value based on the sample size and number of determinants. It provides a more precise indicator of the model's goodness-of-fit, especially when several predictors are included. Using the designated covariance estimation method (Bartlett kernel and Newey-West), the long-run variance calculates the variability of residuals over an extended period. The long-run correlation between the variables is indicated by the long-run variance (0.006). When autocorrelation in the residuals is tested using the Durbin-Watson statistic, results close to 2 indicate no autocorrelation, whereas values substantially below or above 2 point to possible autocorrelation issues. Since the value is close to or around 2, the Durbin-Watson statistics of 1.95 show no serial correlation between the error terms.

Table 6 shows that LRAINFALL (rainfall) and LCO2 (carbon dioxide emissions) were significant at the 5 percent and 1 percent respectively. More specifically, the rainfall coefficient (-0.694) is weakly substantial. In the long run, it is precisely at the traditional significance level of 0.05. This means aquaculture production would drop by 0.694 units for every unit rise in LRAINFALL (rainfall). This result is consistent with the findings of Wahab and Iyiola (2023), who noted that variation in rainfall patterns can damage ecosystems, river flows, and the amount of water in wetlands and estuaries. This may affect fish habitats, especially in areas where freshwater imports are essential to preserving ecological balance. In addition, the negative coefficient may reflect the difficulty in figuring out the ideal rainfall amount to maximize aquaculture output, which might vary depending on several variables like the kind of aquaculture, the region, and certain environmental circumstances.

Potential adaptation strategies for "Recirculating Aquaculture Systems (RAS)" were proposed by Ahmed and Turchini (2021). RAS are environmentally friendly, water-efficient, highly productive intensive farming systems that are not linked to harmful environmental effects like habitat destruction, eutrophication, and pollution of water, biotic depletion, ecological effects on biodiversity due to escapee exotic species and captive fish, disease outbreaks, and parasite transmission. Furthermore, because RAS function in a controlled indoor environment, they are mostly unaffected by weather-related variables such as changes in rainfall, floods, droughts, global warming, cyclones, salinity fluctuations, ocean acidification, and sea level rise. RAS has not yet gained widespread adoption despite its potential and promises, especially in Nigeria, because of its intricate and expensive system designs.

The coefficient of (LCO2) carbon dioxide emissions (1.778) causes a simultaneous rise in aquaculture output of 1.778 percent and is statistically significant at the 0.01 level. This result is in line with the International Federation of Inventors' Associations (IFIA) 2019 report, which stated that 1 billion tons of compound feed are used annually worldwide for fisheries and livestock, of which 16.6 million tons are used as aqua-feed, or buried carbon, in the aquaculture sector. The primary source of CO₂ produced by heterotrophic bacteria is the mineralization of organic materials. Most of the aquaculture organic matter composition is also influenced by dead phytoplankton biomass, fish fecal, feed leftovers, and manure applications. Finding ecologically viable aquaculture is an ongoing effort that can only be accomplished with environmental management tools that pinpoint the aspects related to the production systems and their possible ecological implications. Numerous strategies exist for lowering emissions, such as creating genetically modified breeds appropriate for reduced feed conversion rates, enhancing health, employing more exact feeding techniques, and enhancing farm energy efficiency (Devasena et al., 2022).

4.5 Granger causality tests

When two time series of data, PX and QX, become co-integrated, they must thus be stationary in a linear combination, giving birth to the Granger causality idea (Olaifa et al., 2022). The Granger causality assessment identifies the direction of the correlation between two variables (unidirectional and bidirectional causation). In contrast to bidirectional causality, which holds that if A affects B, then B also causes A, unidirectional causality holds that if variable A influences variable B, then B cannot cause A.

Table 7: Pairwise Granger Causality Tests at Lags 2

S/N	Null Hypothesis (H ₀)	F-Stat.	Prob.	Remarks
1	LTEMP does not Granger Cause LAQUAPRO	0.207	0.818	Accepted
	LAQUAPRO does not Granger Cause LTEMP	0.010	0.991	Accepted
2	LRAINFALL does not Granger Cause LAQUAPRO	1.570	0.273	Accepted
	LAQUAPRO does not Granger Cause LRAINFALL	1.649	0.259	Accepted
3	LCO2 does not Granger Cause LAQUAPRO	0.907	0.447	Accepted
	LAQUAPRO does not Granger Cause LCO2	1.294	0.333	Accepted
4	LRAINFALL does not Granger Cause LTEMP	0.090	0.915	Accepted
	LTEMP does not Granger Cause LRAINFALL	0.615	0.568	Accepted
5	LCO2 does not Granger Cause LTEMP	0.089	0.916	Accepted
	LTEMP does not Granger Cause LCO2	0.356	0.712	Accepted
6	LCO2 does not Granger Cause LRAINFALL	0.992	0.418	Accepted
	LRAINFALL does not Granger Cause LCO2	0.136	0.875	Accepted

Table 7 shows the Granger causality test results. To ascertain if one time series may predict another, Granger causality tests are employed. According to the Null Hypothesis (H_0), there is no Granger causation in the near term between the variables. The Granger causality test F-statistic result indicates how strongly historical values of one variable contribute to the explanation of present values of another. The likelihood of witnessing the test findings under the null hypothesis is shown by the p-value associated with the F-statistic. The choice is based on the p-value. The null hypothesis is failed to be accepted if the p-value is less than the chosen significance threshold, which is typically 0.05. While the FMOLS model yields extremely noteworthy findings, it is unable to account for the causal impact that each variable has on its own. Therefore, to investigate the causal link between the variables, the Granger causality test is employed in this study. Table 7 displays the findings of paired Granger causality tests at lag 2.

There is no proof that historical LTEMP values can be used to forecast LAQUAPRO levels in the future. Given the high p-value (0.818), the null hypothesis cannot be rejected. Likewise, there is no proof that historical LAQUAPRO values indicate future LTEMP levels. Given the high p-value (0.991), the null hypothesis cannot be rejected. There is no proof that historical LRAINFALL values can be used to forecast LAQUAPRO values in the future. Since the p-value (0.273) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LAQUAPRO values can be used to forecast LRAINFALL values in the future. Since the p-value (0.259) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LCO2 values can be used to forecast LAQUAPRO values in the future. Since the p-value (0.447) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LAQUAPRO measurements can be used to forecast LCO2 levels in the future. Since the p-value (0.333) is more than 0.05, the null hypothesis cannot be rejected.

There is no proof that historical LRAINFALL values can be used to forecast LTEMP values in the future. Since the p-value (0.915) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LTEMP values can be used to forecast future LRAINFALL values. Since the p-value (0.568) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LCO2 readings can be used to forecast future LTEMP values. Since the p-value (0.916) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LTEMP measurements can be used to forecast LCO2 levels in the future. Since the p-value (0.712) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LCO2 levels can be used to forecast future LRAINFALL values. Since the p-value (0.418) is more than 0.05, the null hypothesis cannot be rejected. There is no proof that historical LRAINFALL readings can be used to forecast LCO2 levels in the future. Since the p-value (0.875) is more than 0.05, the null hypothesis cannot be rejected.

The null hypotheses are accepted since the p-values in every test performed are higher than the usual significance level of 0.05. This indicates that none of the analysed variable pairings exhibit any hint of Granger causality; in other words, past data on each of these parameters does not provide statistically relevant insight into how the different variables in the study may appear in the future.

4.6 Analysis of variance (ANOVA)

A regression model's analysis of variance (ANOVA) breaks down the variance in the dependent variable that the model explains and the variance brought on by random error.

Table 8: Analysis of Variance (ANOVA)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	23093150860.572	3	7697716953.524	15.220	0.000
Residual	5057723491.142	10	505772349.114		
Total	28150874351.714	13			

The results of the ANOVA between aquaculture production and climate change are displayed in Table 8. The findings reveal that the predictive regression model is statistically significant and that the predictors (temperature, rainfall, and CO₂) in the model collectively have a significant impact on aquaculture production. The F-value of 15.22, with the p-value of 0.000, which is below the alpha threshold of 0.05, indicating statistical significance at the 5% level.

4.7 Graphs illustrating trend analysis

Showing patterns over time utilising analysis of trend charts, often known as run charts, aids in understanding the actual performance of each variable over the periods under consideration. Figure 1 (a-e) displays the trends chart of temperature, CO2, rainfall, and aquaculture production, respectively, in Nigeria from 2009 to 2022.

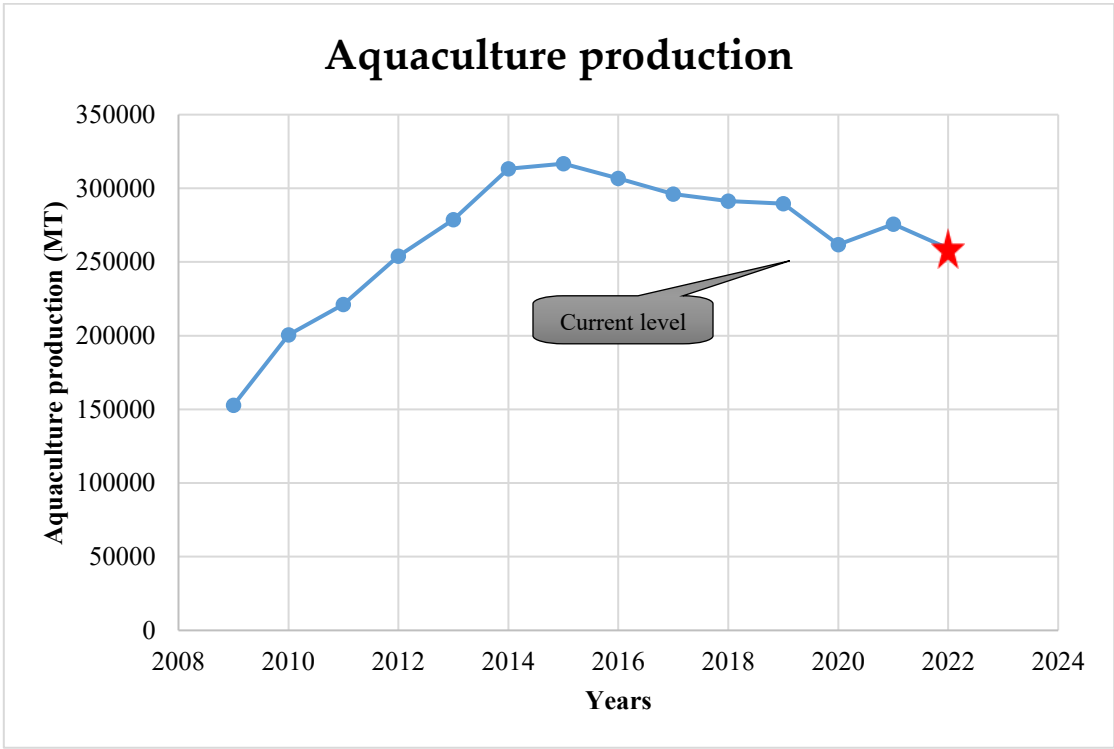


Figure 1a: Trends of Aquaculture production in Nigeria

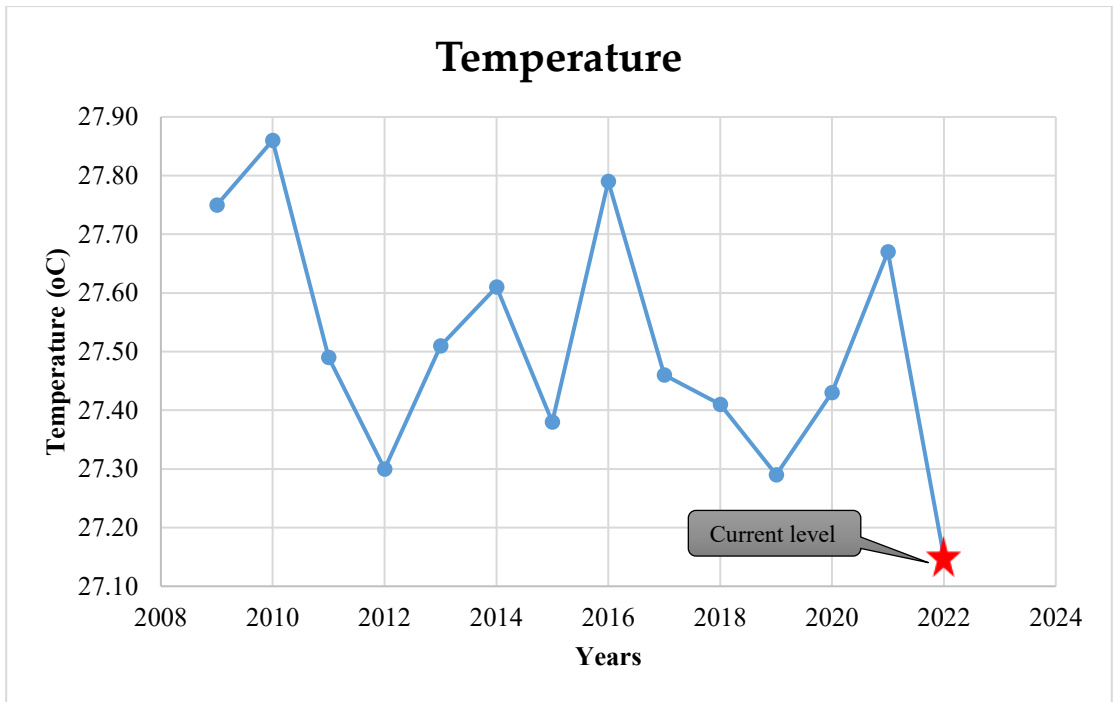


Figure 1b: Trends of Temperature in Nigeria

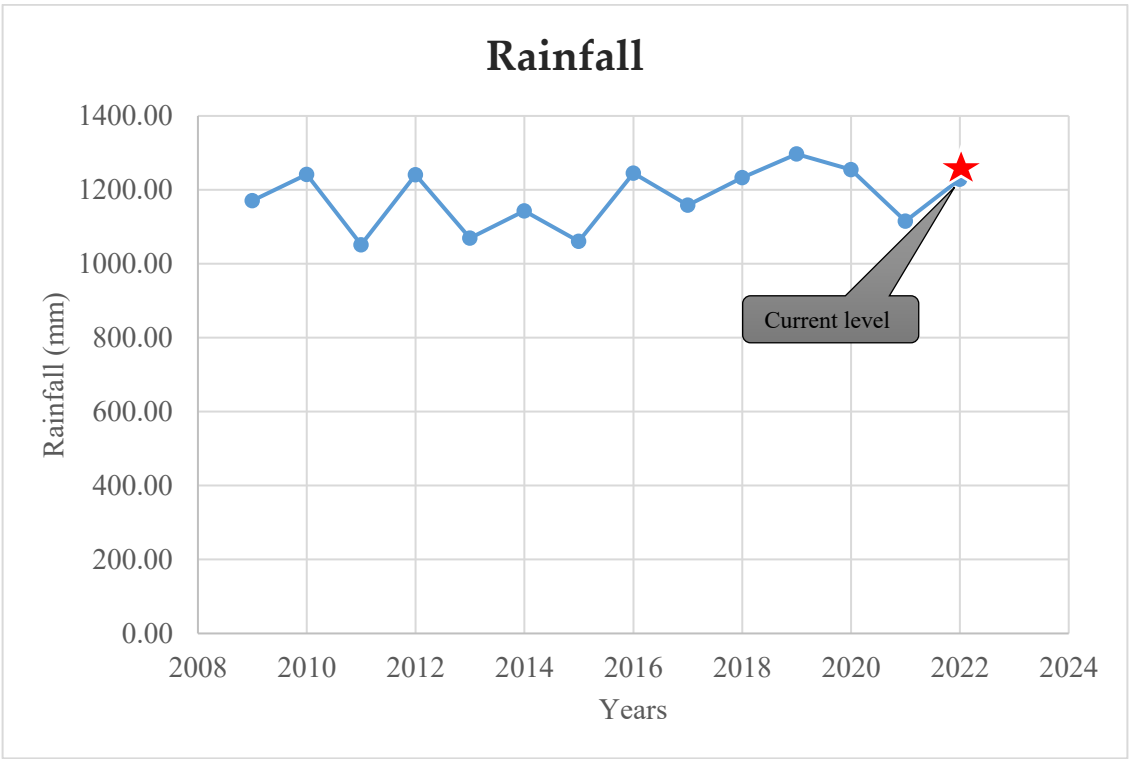


Figure 1c: Trends of Rainfall in Nigeria

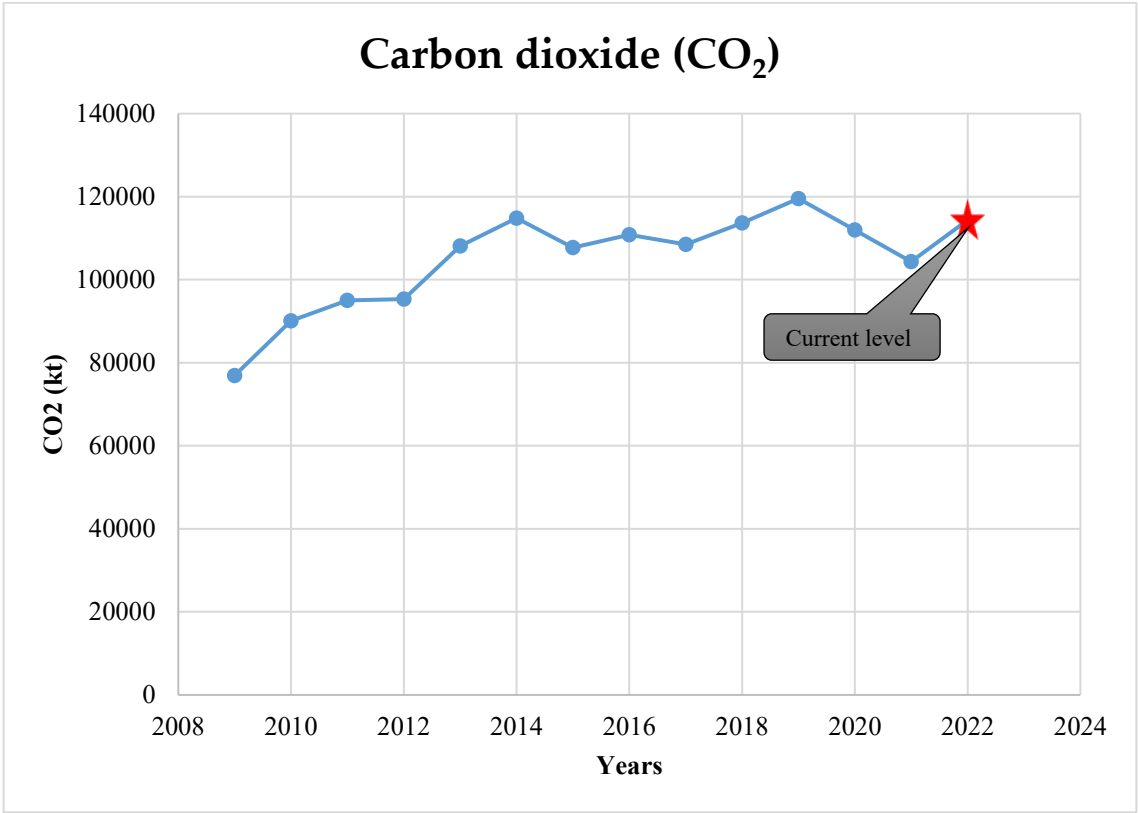


Figure 1d: Trends of Carbon dioxide (CO2) in Nigeria



Figure 1e: Trends of variables used in Nigeria

4.8 Models stability

Using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) of recursive residuals tests with a 95% confidence range, the stability of the models was also investigated.

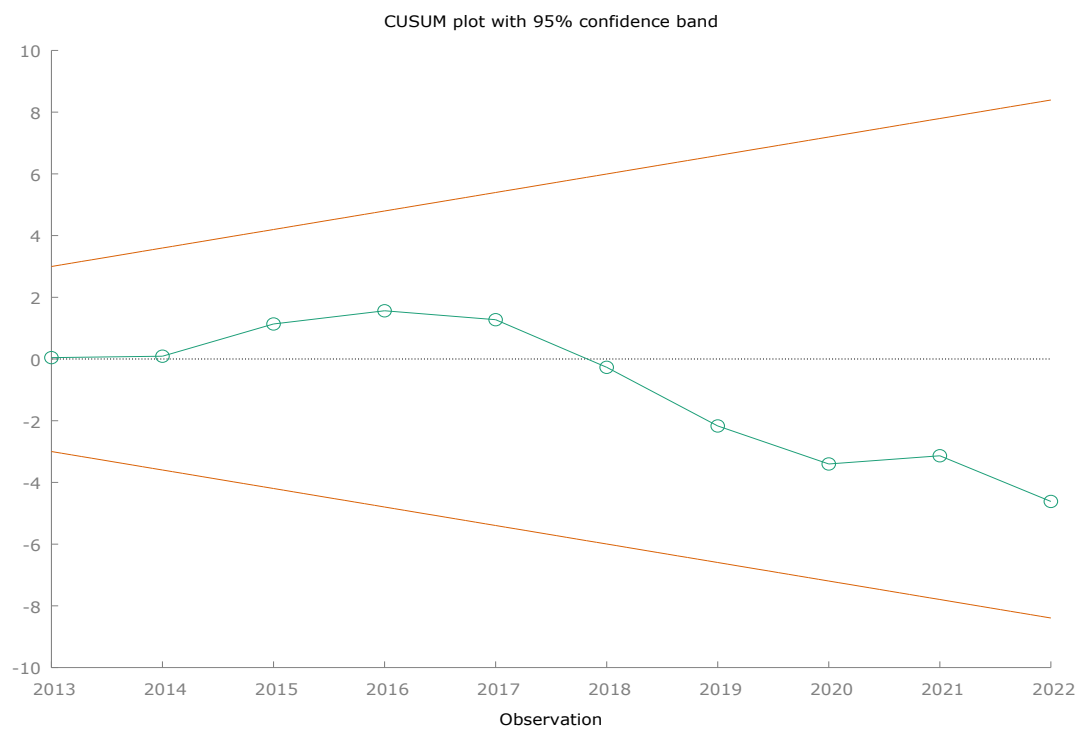


Figure 2a: CUSUM test for aquaculture production

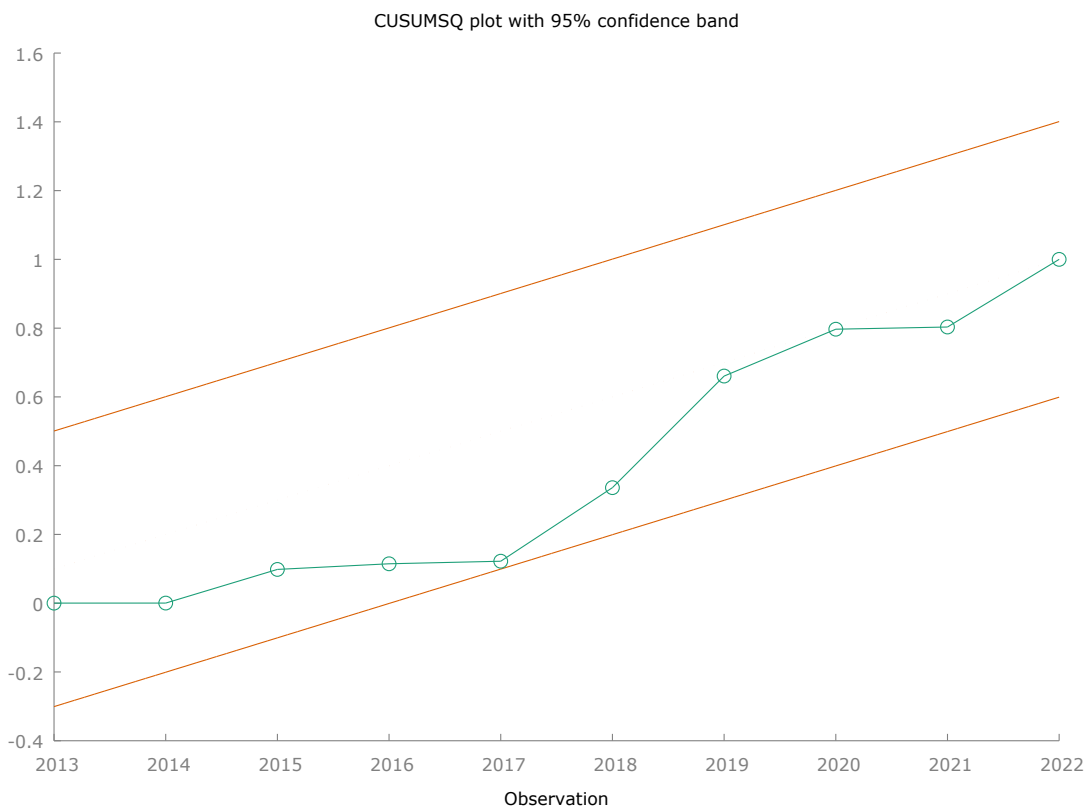


Figure 2b: CUSUMQ of square test for aquaculture production

CUSUM test for stability of parameters shows a mean of scaled residuals of -0.0377733 and σ_{mahat} is 0.0818377 with Harvey-Collier $t(9)$ at -1.45959 with a p-value of 0.1784. The cumulated sum of scaled residuals indicated no value outside the 95% confidence band (Figure 2a). CUSUMSQ test for stability of parameters shows the cumulated sum of squared residuals and indicates no value outside of the 95% confidence band (Figure 2b). The results in Figure 2a and Figure 2b show that the models are stable since both CUSUM and CUSUMSQ for aquaculture production are within the 5% level of significance verge.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This study looked at how climate change is affecting Nigeria fisheries and aquaculture industries. The primary aim of this study is to examine the impact of climate change on aquaculture productivity in Nigeria between 2009 and 2022. The unit root test and FMOLS analysis on aquaculture productivity and independent variables (temperature, rainfall, and CO₂) were utilized to ascertain this influence. ANOVA, the Granger causality test, and correlation analysis were also employed to validate the FMOLS results. All variables were entirely stationary at the first various orders at both ADF and PP, according to the panel unit root test result. The rainfall and carbon dioxide (CO₂) emissions were significant at the 5% and 1% levels, respectively, according to the FMOLS results. Moreover, temperature shows a positively but non-significant association with Nigerian aqua farming production. The Granger causality test found short-run causality for all variables. The primary constraint of this study is a lack of data on aquatic algae cultivation and emissions. Because aquatic plants contribute significantly to the aquaculture sector in Nigeria and globally as well. The addition of this data in Nigeria would result in increased fisheries and aquaculture production. The research therefore, recommends the following policy:

- i. Stringent regulations should be implemented nationally to discourage intense aquaculture in regions with substantial carbon sequestration and promote it in areas with deteriorated soil, such as inland saltwater regions, where the carbon pool is significantly less.
- ii. To better understand and lessen the effects of climate change on Nigeria aquatic resources, fish and aquaculture producers should take a holistic strategy that includes investing in technology, implementing sustainable practices, and building climate resilience.
- iii. To reduce the effects and boost resilience in both human society and natural ecosystems, adaptation to the current and projected climate change is essential. In addition to emission reduction and other climate change mitigation measures, adaptation is now a crucial component.
- iv. Incorporate ecosystem-based adaptive aquaculture strategies for the management of priority resources (like shared pelagic and demersal stocks), ensuring that management measures (like quota systems and technical measures) are harmonized and that the additional risks associated with climate change are taken into consideration.

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Author contributions

Conceptualization: ARA; Methodology: ARA, AH; Data gathering and curation: ARA; Formal analysis: ARA; Investigation and Supervision: AH; Validation: AH; Visualization: ARA, AH; Resources: AH, ARA; Writing original draft: ARA; Review: AH; Editing of the manuscript: ARA, AH. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that there are no conflicts of interests.

Ethical approval

Not applicable.

Informed consent

Not applicable.

Data availability

All data associated with this study will be made available based on the reasonable request to corresponding author.

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