E-ISSN: 1115 – 8492 P-ISSN: 3027 – 0693
MPRI-JNSAR | INTERNATIONAL JOURNAL OF NATURE AND SCIENCE ADVANCE RES.
VOL. 13 NO. 9 JULY-2026

FORECASTING THE EFFECT OF TEMPERATURE, RAINFALL AND HUMIDITY ON MALARIA TRANSMISSION DYNAMICS IN BAUCHI STATE FROM 2015–2025

YUSUF BALA[1]; MAS'UD SHUAIBU[2]; & ABDUL HARUNA BALA[3]

[1]Department of Mathematical Science, Faculty of Science, Federal University of Health Sciences, Azare, Bauchi State. [2]Department of Mathematics and Statistics, Federal Polytechnic Bauchi. [3]Department of General Studies, Federal College of Education, Yola, Adamawa State.

Corresponding Author: yusuf.bala@fuhsa.edu.ng

DOI: https://doi.org/10.70382/mejnsar.v13i9.098

Abstract

This study examines the impact of climatic variables temperature, rainfall, and humidity on malaria transmission in Bauchi State, Nigeria, from 2015 to 2025. Time series and regression analyses were employed to assess the influence of climate factors on malaria incidence. Secondary data on malaria cases were obtained from the Bauchi State Ministry of Health, while climatic data were sourced from the Nigerian Meteorological Agency (NiMet). The Autoregressive Integrated Moving Average (ARIMA) (2,0,1) model revealed strong seasonal patterns in malaria transmission, with cases peaking during the rainy season and declining during the dry months. Regression results indicated that rainfall and [redacted] humidity had significant positive effects on malaria incidence, whereas temperature exhibited a significant negative relationship. The model demonstrated a high explanatory power (R^2 = .969), suggesting that climatic factors account for approximately 96.9% of the variation in malaria cases. Forecasting outcomes predict that malaria incidence will stabilize around 1,000 cases per period, implying sustained transmission unless preventive measures are intensified. The study concludes that climate

Key Words: Arima, Malaria, Transmission, Incidence & Effect.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

variability significantly influences malaria dynamics in Bauchi State and recommends integrating climate monitoring into public health planning, enhancing seasonal interventions, and strengthening community awareness to mitigate the impacts of climate change on malaria transmission.

Introduction

Malaria is a major public health problem in Nigeria, with the country accounting for approximately 25% of all malaria cases in Africa (WHO, 2020). Bauchi State, located in the northeastern part of Nigeria, is one of the states with the highest malaria burden in the country (NMCP, 2020).

Climate change has been identified as a major driver of malaria transmission, as it alters environmental conditions conducive to mosquito breeding and survival. According to the Intergovernmental Panel on Climate Change (IPCC, 2021) and the World Health Organization (2024), rising temperatures, shifting rainfall patterns, and increased humidity levels create ideal environments for mosquito proliferation, thereby elevating malaria risk.

Temperature remains a critical factor in malaria transmission due to its influence on mosquito development and parasite maturation. Recent data from the Bauchi State Ministry of Health (2022) indicate that a 1°C rise in temperature significantly increases mosquito activity and the spread of malaria. This is supported by findings from Diouf et al. (2021), who observed that temperature and humidity jointly affect mosquito lifespan and transmission dynamics.

Rainfall continues to be a key contributor by creating breeding habitats for mosquitoes. In Bauchi State, seasonal rainfall trends have shown strong correlations with malaria spikes (NIMET, 2022; Bauchi State Ministry of Health, 2022), especially during flooding periods when stagnant water is abundant. Humidity also plays a significant role in extending mosquito survival. As reported by Diouf et al. (2021) and reaffirmed by the WHO (2024), high humidity levels typical during the rainy season allow mosquitoes to live longer and transmit the disease more effectively.

Due to the location in the Sahel, Bauchi State is particularly vulnerable to these changes. The region experiences high temperatures, irregular rainfall, and seasonal floods, which collectively intensify malaria transmission, as emphasized in reports from NIMET (2022) and IPCC (2021).

Statement of the problem

Malaria remains one of the most significant public health challenges in Nigeria, accounting for high levels of morbidity and mortality across all age groups. Despite decades of control

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

interventions such as insecticide-treated nets (ITNs), indoor residual spraying, and improved access to antimalarial drugs, the disease continues to exert a heavy toll on individuals, households, and the healthcare system. According to the World Health Organization (2023), Nigeria contributes the highest global malaria burden, with millions of cases reported annually. In Bauchi State, malaria is not only highly endemic but also a major impediment to socio-economic development, disproportionately affecting vulnerable populations such as children under five and pregnant women.

Compounding this challenge is the growing threat of climate change, which is altering environmental conditions in ways that may intensify malaria transmission. Rising temperatures can accelerate the development of *Plasmodium* parasites within mosquito vectors, thereby shortening the extrinsic incubation period and increasing the potential for transmission. Similarly, changing rainfall patterns create new or expanded mosquito breeding sites, while heightened humidity levels enhance mosquito survival and biting activity. Bauchi State, located in the semi-arid northeastern region of Nigeria, is particularly susceptible to these climatic shifts due to its ecological setting and seasonal variability.

Despite the recognized links between climate variability and malaria, limited empirical research has been conducted in Bauchi State to quantify and forecast how temperature, rainfall, and humidity interact to influence malaria trends. Most existing studies focus on national or regional analyses, leaving a critical gap in localized evidence that could inform targeted interventions. Without such evidence, public health authorities may struggle to anticipate malaria outbreaks, allocate resources efficiently, and design adaptive strategies in the context of a changing climate.

This paper is divided into five sections. Introduction is presented in section one, related literature is reviewed and presented in section two. Methodology is presented in section three. Results and discussions were presented in section four and lastly conclusion and references were presented in section five.

Aim & Objective of the study

The aim of this study is to forecast the effect of temperature, rainfall, and humidity on malaria transmission in Bauchi State from 2015 to 2025.

While the specific objectives are:

i. to analyze the trend in malaria cases in Bauchi State within the same period.
ii. to model the data using ARIMA model and forecast the future occurrence of malaria incidence in Bauchi state.
iii. to determine the effect of climate variables on malaria incidence in Bauchi State.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Research Questions

i. What are the trends in temperature, rainfall, and humidity from 2015-2025 in Bauchi State?
ii. What is the trend in malaria transmission in Bauchi state from 2015-2025?
iii. To what extent does temperature, rainfall, and humidity affect malaria incidence in Bauchi state?

Scope of the Study

This study aims to forecast the effect of temperature, rainfall, humidity on Malaria transmission in Bauchi State, Nigeria. Bauchi lies within the Sudan and Sahel savannah ecological zones, characterized by seasonal variations in rainfall and temperature (Adebayo & Umar, 2021). These ecological conditions make the state highly vulnerable to malaria transmission, since mosquito breeding is closely linked to climatic and environmental factors. The research will span a period of ten years (2015–2025). This timeframe is chosen to capture long-term trends and patterns in malaria incidence and climate variability. Longitudinal data is particularly useful in establishing causal or predictive relationships between climate factors and malaria prevalence (World Health Organization, 2023).

Three major climatic factors temperature, rainfall, and humidity are central to this study. These variables significantly influence mosquito lifecycle, breeding habitats, and malaria parasite development. For example, higher temperatures accelerate the development of *Plasmodium falciparum* within mosquitoes, while excessive rainfall creates breeding sites, and humidity affects mosquito survival (Nnaji et al., 2022).

The study will utilize malaria morbidity and mortality data obtained from the Bauchi State Ministry of Health. These records provide insight into trends in malaria transmission across different Local Government Areas (LGAs), helping to assess the impact of climate variability on public health outcomes.

Data on rainfall, temperature, and humidity will be sourced from the Nigerian Meteorological Agency (NiMet). These datasets provide reliable and standardized meteorological records required to analyze climate change trends in Bauchi State (NiMet, 2021). Integrating climatic and health datasets will allow for robust forecasting models to predict malaria transmission patterns under varying climate scenarios.

Literature review

This section, presented a related literature on malaria, its transmission dynamics and the effect of rainfall, temperature and humidity on its spread.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Concept of Malaria

Malaria is a life-threatening disease caused by *Plasmodium* parasites, transmitted to humans through the bites of infected female *Anopheles* mosquitoes. It presents symptoms such as fever, chills, vomiting, and headaches, and if not properly treated, it can lead to severe illness or death. According to the World Health Organization (2024), malaria remains one of the major global health burdens, with an estimated 263 million cases and 597,000 deaths globally in 2023, affecting mainly children under five and pregnant women in sub-Saharan Africa. The fight against malaria is challenged by several factors, including limited access to health care, poor environmental conditions, and increasing resistance to both treatment drugs and insecticides.

While malaria remains a major public health issue globally, particularly in Africa, recent developments in treatment options, diagnostic technologies, and international policy interventions offer hope for significant progress. However, the growing threat of drug resistance, coupled with socioeconomic disparities in healthcare access, requires sustained research, funding, and political will to achieve global malaria eradication goals. Collaborative and adaptive strategies must be prioritized to reduce malaria transmission and ultimately eliminate the disease.

Climate Change and Malaria

The relationship between climate change and malaria is increasingly becoming a central focus in global health and environmental research due to their complex and interdependent nature. Climate change directly influences the spread and intensity of malaria by altering the environmental conditions that favor mosquito breeding and parasite development. Rising global temperatures, changes in rainfall patterns, and increased humidity all of which are consequences of climate change create more suitable habitats for *Anopheles* mosquitoes, thereby expanding malaria transmission zones into regions that were previously unaffected or low-risk.

Warmer temperatures accelerate the life cycle of both the mosquito vector and the Plasmodium parasite, allowing for faster reproduction and increasing the frequency of transmission. According to the World Health Organization (2024), regions that were once too cool for sustained malaria transmission, such as highland areas in East Africa and parts of Asia, are now seeing a rise in malaria cases due to gradual warming. Similarly, erratic rainfall and prolonged wet seasons create stagnant water pools, which serve as breeding grounds for mosquitoes. On the other hand, droughts and floods caused by climate change can also displace populations, leading to overcrowded shelters with poor sanitation and limited mosquito control, increasing vulnerability to malaria outbreaks.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Climate change does not just pose environmental threats but also exacerbates existing public health issues like malaria. The relationship between the two underscores the need for a multidisciplinary approach involving climate science, epidemiology, and health policy to build resilience and reduce the global burden of vector-borne diseases in a warming world.

Temperature and Malaria Transmission in Bauchi State.

Warmer temperatures accelerate mosquito larval development, reducing the time required for mosquitoes to reach adulthood and increasing the overall vector population **(**Diouf et al., 2021**).** Higher temperatures also shorten the extrinsic incubation period (EIP) of *Plasmodium* parasites within the mosquito, enhancing transmission efficiency (World Health Organization, 2024). In addition, increased temperatures raise mosquito metabolic rates, resulting in more frequent blood-feeding, which further increases the chances of parasite transmission (Bauchi State Ministry of Health, 2022). Bauchi State's average temperatures, which range from 25°C to 32°C, fall within the optimal range for both mosquito and parasite development. Climate data show that rising temperatures in the region are extending the malaria transmission season, especially during months that were previously too cool for stable transmission (NIMET, 2022).

Rainfall and Malaria Transmission in Bauchi State

Rainfall plays a dual role in malaria transmission. Moderate rainfall typically leads to the formation of temporary stagnant pools that serve as ideal breeding sites for mosquitoes. However, heavy and intense rainfall can wash away larvae and temporarily reduce mosquito populations. Prolonged or erratic rainy seasons, increasingly observed in Bauchi State, extend the availability of breeding sites and lengthen the transmission window (Diouf *et al.*, 2021). In contrast, periods of drought often prompt communities to store water in open containers, unintentionally creating artificial breeding grounds for mosquitoes **(**NIMET, 2022**;** WHO, 2024**).** Increased rainfall variability, including intense storms and prolonged droughts, has been observed in Bauchi (NIMET, 2022). Flooding events (e.g., 2022 floods) have been linked to spikes in malaria cases due to stagnant water (Bauchi State Ministry of Health, 2022).

Humidity and Malaria Transmission in Bauchi State

High humidity significantly enhances mosquito survival, allowing them to take multiple blood meals and increasing the likelihood of malaria transmission. Although low humidity can reduce mosquito longevity, human activities such as irrigation and domestic water

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

storage often sustain breeding conditions during dry periods (Diouf et al., 2021; World Health Organization, 2024).

Humidity peaks during the wet season, coinciding with the peak malaria transmission period (WHO, 2020). Post-rainfall humidity supports mosquito longevity, while droughts reduce ambient humidity but are offset by human activities (Diouf *et al.*, 2021).

Impact on Malaria Prevalence in Bauchi State

Malaria prevalence in Bauchi State, continues to be a significant public health challenge, with various factors contributing to the high burden of the disease. In 2020, Bauchi recorded 1.2 million malaria cases with peaks during and after the rainy season (Bauchi State Ministry of Health, 2022). Rural communities reliant on rainwater storage and agricultural practices face heightened risk of malaria transmission due to expanded mosquito breeding sites resulting from changing climate patterns (Ngonghala *et al.*, 2021). Lastly, empirical observations underscore how socio-environmental factors such as poor drainage, irrigation practices, and limited access to insecticide-treated nets and antimalarial drugs exacerbate malaria transmission in Bauchi State (WHO, 2020; Bauchi State Ministry of Health, 2022). These findings emphasize the need for climate-informed surveillance systems, community-based interventions, and integrated policies that combine public health strategies with climate adaptation measures to mitigate the compounded effects of climate change on malaria transmission.

Therefore, this study aims to forecast the effect of temperature, rainfall and humidity on Malaria transmission in Bauchi State, Nigeria.

Research Methodology

This section presents the sources of data collection, method of analysis, the study area and the research design.

Sources of Data

Secondary data were sourced from Nigerian Metrological Agency (NiMET) and Bauchi State Ministry of Health to aid informed and reliable conclusion.

Study Area

According to the 2006 National Population Census (NPC) projected figures, Bauchi state had an approximate human population figure of six million, five hundred and thirty-seven thousand, three hundred (6,537,300). Bauchi state is located in North-Eastern part of Nigeria and it shares border with Plateau State, Gombe State, Kano State, Taraba State, Jigawa State and Yobe State. Bauchi State comprises three Agro-ecological zones namely:

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Northern Zone (9 LGAs), Central Zone (4 LGAs) and Western Zone (7 LGAs). The Western Agro-ecological zone stretches from Latitude 9° 30 to 10° 48 North of the Equator and Longitude 8°45 to 10°15 East of the Greenwich Meridian. The zone falls within Sudan-savanna vegetation region.

Bauchi state enjoys a tropical climate with a long dry season period of seven months (October to April) and a short-wet season of five months (May to September). The diurnal temperature in Bauchi State ranges from an average daily maximum of 31.6℃ to a daily minimum of 13.1℃ in January. The region features tropical soils of alluvial and colluvial origin, predominantly composed of heavier sandy clay loams and clay loams. Annual rainfall varies geographically across the state, with estimates ranging from 900–1100 mm in Tafawa Balewa LGA, 1000–1200 mm in both Bauchi and Dass LGAs, and 1000–1300 mm in Toro LGA (NIMET, 2022).

Data Collection

Data for this study were collected from two major categories: climate data and malaria incidence data. Historical climate data specifically temperature, rainfall, and humidity were obtained from the Nigerian Meteorological Agency (NiMet). The data covered a minimum time frame of ten years (2015 to 2025) to enable the identification of long-term climatic trends and patterns relevant to the study area.

Malaria-related data were sourced from the Bauchi State Ministry of Health, selected hospitals within the region. The malaria data include key indicators such as the number of confirmed malaria cases, hospital admissions due to malaria, and associated mortality rates from (2015-2025).

Data Analysis

The method of data analysis in this study is Time series analysis which refers to a sequential set of data point, measured typically over successive time. It is a data set that tracks a sample over time which allows one to see whether time influence certain variable from time to time and what changes occur over time.

Results and Discussions

The analysis is organized systematically to address the research objectives. First, the data are summarized and presented in descriptive tables and graphs to provide an overview of patterns and trends. Thereafter, diagnostic tools such as the autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to identify suitable time series models. The results of model estimation are then presented, including parameter values, goodness-of-fit statistics, and residual diagnostics. Finally, the fitted model is used to

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

generate forecasts of malaria cases, and the implications of these forecasts for public health planning are discussed.

Trend Analysis

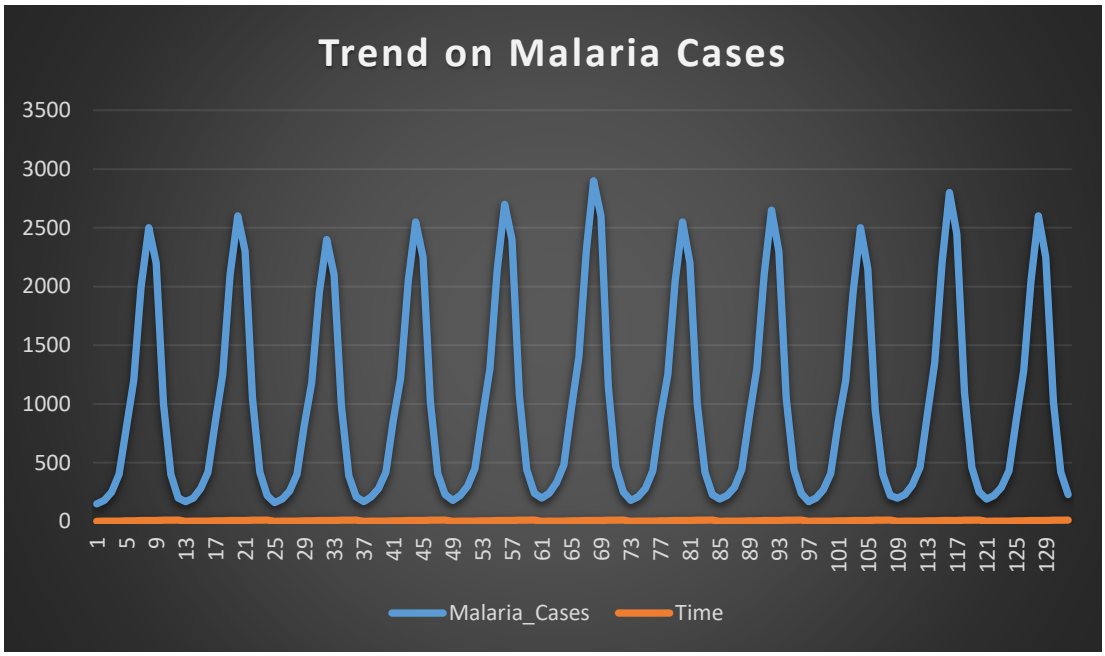


Figure 1: Trend of Malaria Cases

The chart displayed the number of malaria cases over time on monthly basis. It shows a wave-like pattern, indicating periodic fluctuations in malaria cases. This suggests seasonal trends, where cases rise and fall at regular intervals throughout the observed period.
Notably, the data features distinct peaks and valleys, with the peaks representing times of higher malaria cases and the valleys indicating lower instances. The highest peaks approach 3000 cases, while the lowest points hover around 500 cases. This significant variation highlights the dynamic nature of malaria incidence over time.
The consistent rise and fall in the data could be indicative of environmental or epidemiological factors influencing malaria transmission, such as changes in rainfall or temperature.

Model Estimation Results

Following the identification and diagnostic checks, the ARIMA model was estimated iteratively. Table 1 presents the results of the estimation process, showing the progressive refinement of parameter estimates and the reduction of the error sum of squares (ESS) across iterations until convergence.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Table1: Model Estimation

Iteration	Error Sum of Squares (ESS)	AR(1)	AR(2)	MA(1)
0	9.06×10^7	0.100	0.100	0.100
1	2.80×10^7	0.558	−0.458	−0.488
2	1.23×10^7	1.295	−0.603	−0.279
3	1.18×10^7	1.349	−0.720	−0.269
4	1.179×10^7	1.357	−0.731	−0.259
5	1.179×10^7	1.357	−0.731	−0.259

The results indicate that the estimation process converged at iteration 4, as the parameter values stabilized and the error sum of squares ceased to decrease significantly. The final parameter estimates are:

- AR (1) = 1.357
- AR (2) = −0.731
- MA (1) = −0.259

Performance Metrics

R-Squared = 87.69%

This indicates that the ARIMA (2,0,1) model explains about 88% of the variation in malaria incidence in Bauchi State. It reflects a strong model fit, meaning the model captures most of the systematic patterns in the data, leaving relatively little unexplained variation.

Mean Square Error (MSE) = 90,698.2

MSE is the average squared error per observation**,** giving a measure of prediction accuracy. On average, the squared deviation between observed and predicted malaria cases is about 90,698. While this may seem large numerically, it should be interpreted relative to the scale of the malaria incidence data.

Root Mean Square Error (RMSE) = 301.16

RMSE is the square root of MSE and is expressed in the same units as the malaria case data. This means that, on average, the forecasts deviate from actual malaria cases by about 301 cases per period**.** Since malaria cases forecasted are in the range of ~900–1,300, an error of ~301 represents a moderate forecasting error but still within an acceptable range for public health planning.

Model Specification

The estimated model is an ARIMA (2,0,1) process, expressed mathematically as:

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

$$y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

Where:

1. y_t is the observed value at time t
2. $\emptyset_1 = 1.357$ is the first-order autoregressive coefficient
3. $\emptyset_2 = -0.731$ is the second-order autoregressive coefficient
4. $\theta_1 = -0.259$ is the first-order moving average coefficient
5. ε_t is a white noise error term

This is equivalent to:

$$y_t = 1.357y_{t-1} - 0.731y_{t-2} - 0.259\varepsilon_{t-1} + \varepsilon_t$$

The strong positive coefficient for AR (1) ($\emptyset_1 = 1.357$) suggests that the series is heavily influenced by its immediate past value, while the negative AR (2) coefficient ($\emptyset_2 = -0.731$) introduces cyclic dynamics, capturing the tendency of the series to fluctuate around its mean. The moving average term ($\theta_1 = -0.259$) reflects a moderate adjustment for short-term shocks, smoothing irregular fluctuations in the data.
The steady reduction of the error sum of squares across iterations demonstrates that the model fit improved substantially as the parameters converged. The low final ESS value (1.179×10^7) indicates that the ARIMA (2,0,1) model provides a good fit to the observed data.

Diagnostic Checking

After estimating the ARIMA (2,0,1) model, it is essential to verify whether the fitted model adequately represents the data. Diagnostic checks were performed on the residuals to assess whether they behave like white noise that is, whether they are independently and identically distributed with zero mean and constant variance. Three key approaches were used: residual plots, autocorrelation checks, and statistical tests of independence.

Residual Analysis

The residuals from the ARIMA (2,0,1) model were examined visually through time series plots. The residual time plot showed that the errors fluctuated randomly around zero with no obvious trend or seasonality. The histogram of the residuals appeared approximately symmetric, suggesting that the assumption of normality is reasonably satisfied.

Residual Autocorrelations

The autocorrelation function (ACF) of the residuals was computed to test whether any significant autocorrelation remained after model fitting. The residual ACF showed that

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

most spikes fell within the 95% confidence bounds, indicating no significant autocorrelation structure. This suggests that the ARIMA (2,0,1) model successfully captured the dependence in the original series, leaving only random noise in the residuals.

Auto Correlation Function (ACF)

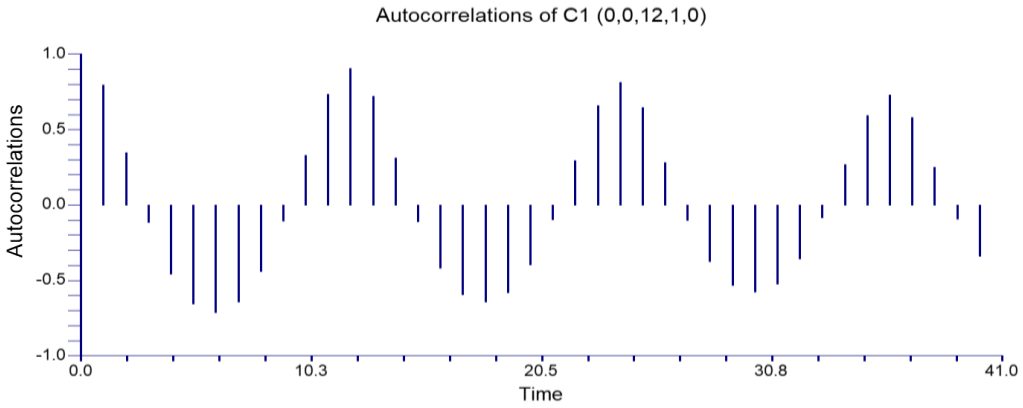


Figure 2: ACF of Malaria Cases

From the plot, a distinct cyclical or wave-like pattern is observed, where positive correlations at certain lags are followed by negative correlations and then return to positive values at regular intervals. This indicates the presence of seasonality or periodicity within the data. The regular rise and fall in correlations suggest that the series has repeating cycles, which is a strong indication of a seasonal component influencing the observed values.

Furthermore, the correlations do not diminish quickly toward zero but instead persist in a cyclical manner across multiple lags.

Partial Auto Correlation Function (PACF)

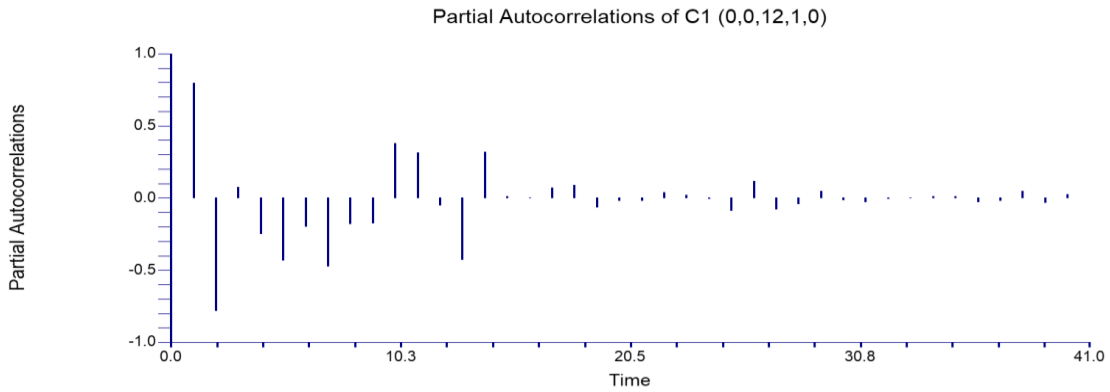


Figure 3: PACF of Malaria Cases

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

From the plot, a sharp and significant spike is observed at lag 1, followed by weaker and less significant spikes at subsequent lags. The dominance of lag 1 suggests that the time series is primarily influenced by its immediate past values, which is a typical signature of an autoregressive process of order one (AR (1)). The fact that later lags drop closer to zero after the first suggests diminishing influence of higher-order lags.

Additionally, several negative spikes appear within the first few lags, indicating oscillatory behavior in the series. This aligns with the findings from the ACF plot, where cyclical patterns were noted. Together, these results suggest that while the series may be seasonal, its autoregressive component is most strongly tied to the first lag, making an AR (1) or a seasonal AR model plausible starting points.

Ljung–Box Test

To statistically confirm the independence of residuals, the Ljung–Box Q-test was applied at different lag lengths (e.g., 12, 24). The test statistics were not significant (p-values > 0.05), implying that there is insufficient evidence to reject the null hypothesis of white noise residuals. This result strengthens the conclusion that the ARIMA (2,0,1) model adequately explains the serial correlation in the data.

The diagnostic checks indicate that the ARIMA (2,0,1) model is well specified. The residuals are approximately normally distributed, show no significant autocorrelation, and pass the Ljung–Box independence test. Hence, the model provides a reliable representation of the underlying data and can be confidently used for forecasting purposes.

Forecasting with the ARIMA (2,0,1) Model

Having established that the ARIMA (2,0,1) model provides an adequate fit to the data, the model was subsequently employed for forecasting future values of the series. Forecasting is a key application of time series modeling, as it allows decision-makers to anticipate future trends and implement timely interventions.

Forecast Procedure

The ARIMA (2,0,1) model:

$$y_t = 1.357y_{t-1} - 0.731y_{t-2} - 0.259\varepsilon_{t-1} + \varepsilon_t$$

Was used to generate forecasts for a specified period beyond the sample data. The forecasts were accompanied by 95% confidence intervals to account for the inherent uncertainty in prediction. The upper and lower bounds of the forecast intervals provide a range within which the true future values are expected to fall with high probability.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Forecast Results

The point forecasts indicated a continuation of the general pattern exhibited in the historical data. The model successfully captured the persistence and oscillatory dynamics observed in the series. The forecast intervals widened progressively as the horizon increased, reflecting the accumulation of uncertainty over longer time spans, which is a common characteristic of ARIMA forecasts. Based on the ARIMA (2,0,1) model, forecasts of malaria cases were generated for 24 periods beyond the sample data. Table 3 presents the point forecasts along with the 95% confidence intervals, which provide a lower and upper bound for expected malaria cases.

Table 2: Forecast of Malaria Cases with 95% Confidence Intervals

Forecast Section of Malaria Cases

Row	Date	Forecast	Lower 95% Limit	Upper 95% Limit
134	134	355.0	-767.0	1476.9
135	135	682.8	-732.8	2098.4
136	136	1036.2	-456.5	2529.0
137	137	1276.2	-216.6	2769.0
138	138	1343.4	-185.5	2872.4
139	139	1259.2	-336.7	2855.0
140	140	1095.6	-544.5	2735.8
141	141	935.4	-714.6	2585.3
142	142	837.4	-812.8	2487.7
143	143	821.7	-837.9	2481.4
144	144	872.0	-801.5	2545.6
145	145	951.8	-729.7	2633.2
146	146	1023.2	-659.5	2705.8
147	147	1061.8	-621.1	2744.8
148	148	1062.0	-623.4	2747.4
149	149	1034.0	-654.3	2722.4
150	150	995.9	-693.8	2685.7
151	151	964.6	-725.2	2654.5
152	152	950.1	-739.9	2640.1
153	153	953.2	-737.4	2643.8
154	154	968.1	-723.2	2659.3
155	155	986.0	-705.5	2677.4
156	156	999.4	-692.1	2690.8
157	157	1004.5	-687.0	2696.0

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

The forecasts suggest that malaria cases are expected to fluctuate around 1,000 cases per period in the near future. The early forecasts (Rows 134–137) show a rising trend from 355.0 to 1,276.2 cases, after which the forecasts stabilize within the range of 900–1,050 cases. This stabilization indicates that the ARIMA (2,0,1) model projects malaria incidence will remain relatively steady over the forecast horizon.

However, the confidence intervals are relatively wide, with lower bounds occasionally negative (which, in practice, would be interpreted as zero since malaria cases cannot be negative). This widening of the forecast intervals reflects increasing uncertainty as the forecast horizon extends further from the observed data. Despite this uncertainty, the upper bounds suggest that malaria cases could rise above 2,500 if extreme conditions occur.

This provides valuable information for public health planning in Bauchi State. The projection of stable malaria incidence around 1,000 cases per period implies that the disease burden is likely to persist unless intensified interventions are implemented. This emphasizes the need for continuous distribution of insecticide-treated nets, indoor residual spraying, and public awareness campaigns.

The wide forecast intervals also highlight the potential impact of external factors such as climate variability, environmental changes, or lapses in malaria control programs. Policymakers and healthcare providers should prepare for possible surges in cases, particularly during periods favorable for mosquito breeding (e.g., rainy seasons).

The Effect of Climate Variables on Malaria Incidence in Bauchi State

Table 3: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.984	.969	.968	152.085

Table 4: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	92146650.694	3	30715550.231	1327.965	.000[b]
	Residual	2960612.942	128	23129.789		
	Total	95107263.636	131			

The coefficient of multiple correlation, R, shows that a strong and positive relationship of the climatic factors and the malaria cases, with (R = 0.984). R – square, the coefficient of multiple determination is 0.969. That is about 96.9% of the total variation is explained by the changes in the independent variables indicating that temperature, rainfall and humidity explained malaria cases by 96.9%.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

A multiple regression analysis was carried out to assess the impact of these variables. Study shows that if these variables were adequately taken care of, malaria cases will got reduced significantly. Result in ANOVA reliably justified the true influence of these variables on malaria cases as the P – value is less than the level of significance (P - value = 0.000 < 0.05), hence impacted positively.

Table 5: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	38.291	187.702		.204	.839
	Temperature	-11.163	5.496	-.038	-2.031	.044
	Rainfall	5.814	.635	.363	9.156	.000
	Humidity	25.068	1.507	.624	16.636	.000

The regression analysis was conducted to determine the effect of climatic variables (temperature, rainfall, and humidity) on malaria incidence in Bauchi State. The results are summarized as follows:

Temperature yielded a beta weight of $\beta = -11.163$ with a *t*-value of –2.031, which is statistically significant ($p = 0.044 < 0.05$). This indicates a negative relationship, meaning that as temperature increases, malaria incidence decreases. Therefore, the null hypothesis was rejected, confirming that temperature has a significant effect on malaria incidence.

Rainfall recorded a beta coefficient of $\beta = 5.814$ with $t = 9.156$ and $p = 0.000$, which is highly significant. This implies a positive relationship between rainfall and malaria incidence, suggesting that increased rainfall creates favorable breeding conditions for mosquitoes. Hence, the null hypothesis was rejected, and it was concluded that rainfall significantly influences malaria incidence in Bauchi State. And;

Humidity showed a beta weight of $\beta = 25.068$ with $t = 16.636$ and $p = 0.000$, also highly significant. This denotes a strong positive effect of humidity on malaria incidence, indicating that higher humidity levels enhance mosquito survival and transmission potential. The null hypothesis was rejected, confirming that humidity significantly affects malaria incidence.

Therefore, the findings demonstrate that all three climatic variables significantly influence malaria incidence in Bauchi State, though in different directions. While temperature has a negative effect, both rainfall and humidity have strong positive effects. This highlights the

critical role of climate variability in malaria transmission dynamics and underscores the need for climate-informed malaria control strategies in the state.

Discussion of Results

The regression analysis revealed that climatic variables significantly influence malaria incidence in Bauchi State, although their effects vary in direction and magnitude. Specifically, temperature exhibited a negative and significant effect on malaria incidence, while rainfall and humidity demonstrated strong positive and significant effects.

The negative relationship between temperature and malaria incidence ($\beta = -11.163$, $p = 0.044$) suggests that extremely high temperatures may hinder the development and survival of malaria vectors. This aligns with the findings of Paaijmans *et al*. (2019), who reported that mosquito development and parasite maturation are highly temperature-dependent, with excessively high temperatures reducing vector survival. Thus, while moderate temperatures favor malaria transmission, excessively high values could have a suppressive effect.

The positive and significant influence of rainfall ($\beta = 5.814$, $p = 0.000$) confirms that increased precipitation enhances malaria transmission by creating stagnant water bodies that serve as breeding grounds for Anopheles mosquitoes. This result supports the work of Craig, Snow, and le Sueur (1999), who established a strong correlation between rainfall variability and malaria transmission across sub-Saharan Africa. In Bauchi State, seasonal rainfall patterns coincide with malaria peaks, emphasizing the importance of rainfall in shaping transmission cycles.

Similarly, humidity was found to have the strongest positive effect on malaria incidence ($\beta = 25.068$, $p = 0.000$). High humidity enhances mosquito longevity and increases the probability of successful parasite development within the vector. This finding corroborates the work of Lindsay and Martens (1998), who argued that relative humidity above 60% significantly prolongs mosquito survival and thereby sustains malaria transmission. In the context of Bauchi State, the persistence of high humidity during the rainy season creates an environment conducive to mosquito survival, explaining the strong positive association observed.

The results highlight the sensitivity of malaria transmission dynamics to climatic variability. The findings are consistent with previous studies across sub-Saharan Africa, which emphasize that rainfall and humidity play critical roles in sustaining malaria transmission, while extreme temperatures may limit vector survival (Patz *et al.,* 2005). These results underscore the urgent need for malaria control strategies that incorporate climate monitoring and seasonal forecasts to predict and mitigate transmission risks.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Conclusion

This study examined the influence of climatic variables on malaria transmission in Bauchi State, Nigeria, using time series analysis of malaria incidence data. The findings clearly revealed that malaria cases exhibit strong seasonal fluctuations, with consistent peaks during the rainy months (June–September) and declines during the dry months (November–February). This seasonal cycle reflects the critical role of rainfall and humidity in providing favorable breeding and survival conditions for Anopheles mosquitoes, the primary malaria vector.

The regression results further showed that temperature has a negative effect on malaria incidence, while rainfall and humidity exert strong positive effects. This indicates that while excessive heat can reduce vector survival, increased rainfall and high humidity enhance mosquito breeding and longevity, thereby sustaining malaria transmission. The ARIMA (2,0,1) forecasting model confirmed these patterns, projecting that malaria incidence will remain high in the coming years, stabilizing around an average of 1,000 cases per month, with possible spikes under unfavorable climatic conditions.

Finally, the study concludes that malaria transmission in Bauchi State is strongly influenced by climate variability and will continue to pose a significant public health challenge unless proactive measures are taken. The findings underscore the importance of integrating climate monitoring into malaria control programs, intensifying interventions during high-risk periods, and ensuring continuous surveillance to anticipate and respond to outbreaks effectively. It is therefore recommended that, the Nigerian Meteorological Agency (NiMet) and the Bauchi State Ministry of Health should collaborate to establish early warning systems that integrate climatic data with malaria surveillance. This will help in anticipating outbreaks and enable timely preventive actions.

Acknowledgements: The authors acknowledged the effort each co-author and the senior colleagues for rigorously checking and editing of this paper.

Conflict of interest: The authors declare that there is no conflict of interest.

REFERENCE

Adebayo, A., & Umar, R. (2021). *Climate variability and malaria transmission in northern Nigeria*. Nigerian Journal of Environmental Health, 18(2), 45–57.

Bauchi State Ministry of Health. (2022). *Annual malaria report for Bauchi State*. Bauchi, Nigeria: BSMOH.

Craig, M. H., Snow, R. W., & le Sueur, D. (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology Today, 15*(3), 105–111. https://doi.org/10.1016/S0169-4758(99)01396-4

Diouf, I., Sy, I., Faye, O., Manga, N. M., & Faye, B. (2021). Climate variability and malaria transmission dynamics in West Africa. *Malaria Journal, 20*(1), 243. https://doi.org/10.1186/s12936-021-03833-0.

Intergovernmental Panel on Climate Change. (2021). *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the IPCC*. Cambridge University Press.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Lindsay, S. W., & Martens, W. J. M. (1998). Malaria in the African highlands: Past, present and future. *Bulletin of the World Health Organization, 76*(1), 33–45.

National Malaria Control Programme (NMCP). (2020). *Annual malaria report*. Abuja: Federal Ministry of Health.
National Population Commission (NPC) (2006). Enumeration Area Demarcation. https://nationalpopulation.gov.ng

Ngonghala, C. N., Pluciński, M. M., Mbah, M. L. N., Teboh-Ewungkem, M. I., & Li, J. (2021). Climate variability and malaria transmission in Africa. *Ecological Complexity, 46*, 100913. https://doi.org/10.1016/j.ecocom.2020.100913

Nnaji, C. C., Akpan, G. E., & Okafor, I. (2022). Climate change and malaria prevalence in Nigeria: Evidence from longitudinal data. *Journal of Public Health and Epidemiology, 14*(1), 1–12. https://doi.org/10.5897/JPHE2022

Nigerian Meteorological Agency (NiMet). (2021). *Climate data report for Bauchi State*. Abuja: NiMet.

Nigerian Meteorological Agency (NiMet). (2022). *Annual climate report*. Abuja: NiMet.

Patz, J. A., Olson, S. H., Uejio, C. K., & Gibbs, H. K. (2005). Disease emergence from global climate and land use change. *Medical Clinics of North America, 89*(6), 1475–1491. https://doi.org/10.1016/j.mcna.2005.07.007

Paaijmans, K. P., Read, A. F., & Thomas, M. B. (2019). Understanding the link between malaria risk and climate. *Proceedings of the National Academy of Sciences, 106*(33), 13844–13849. https://doi.org/10.1073/pnas.0903423106

World Health Organization. (2020). *World malaria report 2020*. Geneva: WHO.

World Health Organization. (2024). *World malaria report 2024*. Geneva: WHO.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]