

Research Article

Seasonality, Temporal Persistence and Climate Sensitivity of Malaria Occurrence in Kaduna North, Nigeria

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ABSTRACT

In this study, monthly data on malaria incidence and climate variables in the Kaduna North Local Government Area of Nigeria were investigated between January 2018 and December 2025. The variables included monthly rainfall, relative humidity (RH), maximum temperature (Tmax), minimum temperature (Tmin), and malaria prevalence. These variables were analyzed using descriptive climatology, the Seasonal Mann-Kendall test, the Seasonal Sen slope test, lagged Pearson and Spearman correlation, Seasonal and trend adjustment with false discovery rate correction, and negative binomial regression with autoregressive terms. Seasonal differences were evaluated using Welch's t test, the Mann-Whitney U test, effect size, and STL decomposition. There was a significant decrease in rainfall ($p=0.0023$), but there was an increase in Tmax ($Z=3.393$, $p=0.0007$; seasonal Sen slope ≈ 0.119 °C per year). There was a strong increase in malaria incidence from 5,688 cases in 2018 to 48,112 cases in 2024 and a decline to 32,673 in 2025. After common seasonality and trends were removed, RH (lag 0) and Tmin (lag 2 months) were significant for malaria. In the final autoregressive negative binomial model, only the RH remained significant (IRR=1.053, 95% CI 1.018-1.089, $p=0.0024$), but this association disappeared when 2025 was excluded, indicating sensitivity to anomalous RH observations. Previous-month malaria markedly improved the model fit and removed residual serial dependence. The wet-season malaria cases averaged 2,499.75 cases, which was 2.44 times the dry-season mean. These findings indicate that malaria dynamics in Kaduna North are dominated by seasonality and temporal persistence, with climate effects that are context- and model-dependent. Climate-informed surveillance should therefore combine climatic indicators with recent case history and seasonal preparedness.

ARTICLE HISTORY

Submitted 10 September 2026

Accepted 24 October 2026

Published 29 October 2026

GUEST EDITOR

A. M. Ahmed

KEYWORDS

Malaria; climate variability; relative humidity; seasonal Mann-Kendall test; negative binomial regression; Kaduna North; Nigeria

1 Introduction

Malaria remains among the most important vector-borne diseases globally and is especially concentrated in sub-Saharan Africa (Oladipo et al., 2022). The World Health Organization estimated 263 million malaria cases and 597,000 deaths in 2023, with the African Region accounting for approximately 94% of cases and 95% of deaths (World Health Organization (WHO), 2024). Nigeria remains among the countries contributing the greatest absolute share of this burden (I. Abubakar et al., 2022). The persistence of malaria has consequences beyond mortality because repeated infection contributes to morbidity, school and work absenteeism, household expenditure on treatment, pressure on health facilities, and losses in productivity. These burdens make the identification of locally relevant environmental and temporal determinants important for surveillance and targeted control (Abdulkarim et al., 2023; Bajoga et al., 2019).

Malaria transmission is intrinsically climate sensitive because the mosquito vector and Plasmodium parasite are ectothermic organisms whose development and survival respond to environmental conditions (Chapotera et al., 2025). Rainfall can create or replenish puddles, drains, pools, and other aquatic habitats required for Anopheles oviposition and larval

development, although intense rainfall may also flush immature stages from some habitats (Asori et al., 2023). Temperature affects mosquito development, adult survival, biting rates, and the development of parasites, whereas relative humidity affects the longevity and activity of adult mosquitoes (Tahir et al., 2023). Notably, these associations are not always linear: the suitability based on temperature may initially increase before finally decreasing with increasing stress from temperature (Mordecai et al., 2013, 2019). Moreover, dynamic mosquito models have shown that the impact of temperature on juvenile development and adult survival is critical for transmission capacity (Lunde et al., 2013).

Climate drivers of malaria transmission also occur across various time scales. While rainfall influences vector density only once habitats have formed and larvae have completed development, temperature affects both the maturation of the mosquito and the incubation period of the parasite within the mosquito host (Bakare et al., 2026). There is also a lag between mosquito biting, illness onset, care seeking, and notification of cases. Therefore, a case of malaria recorded in one particular month may be more strongly associated with the climate of the preceding months than with the concurrent climate (Asori et al., 2023). Empirical evidence increasingly shows lagged

effects of climate on malaria incidence, and in recent studies, differences in the most influential climatic drivers depending on ecology, season, and lag have been highlighted (Rubuga et al., 2024; Santos-Vega et al., 2022, 2023; Yamba et al., 2023).

However, climate does not function on its own. The manifestation of climate suitability is influenced by drainage, land use, irrigation, vegetation, urbanization, population density, socioeconomic factors, housing, human movement, and the accessibility of preventive and curative measures. Urbanization and population density may influence the pattern of parasite prevalence (Kabaria et al., 2017), whereas irrigation and the presence of perennial water sources can ensure the presence of vector breeding grounds beyond the rainy season (Hawaria & Kibret, 2023; Kibret et al., 2019; Zhou et al., 2022). Socioeconomic factors may further contribute to the risk of disease exposure and the ability to prevent and treat it (Atusingwize et al., 2025; Degarege et al., 2019). Such interactions result in the spatial heterogeneity of malaria-climate linkages and in the inapplicability of associations estimated at national or regional levels for specific cities or LGAs.

Northern Nigeria is a good candidate for studying seasonal climate-malaria associations because of the concentration of rainfall during a particular wet season and then the subsequent dry season period. This seasonality gives rise to annual cycles of surface water, vegetation, humidity, and temperature, which might affect vector ecology. Malaria seasonality in relation to climate factors, including rainfall, temperature, and humidity, has been reported to be related across Sub-Saharan Africa (Yamba et al., 2023). Similar relationships have been documented in Nigeria (Ekpa et al., 2023; Okunlola & Oyeyemi, 2019). In Kaduna State, surveillance has revealed large temporal variations in malaria cases (Bajoga et al., 2019), whereas investigations in Kaduna State and surrounding areas have revealed that weather and the environment could affect the observed disease patterns (Burga & Mohammed, 2025; Suleiman et al., 2021).

Kaduna North LGA comprises one of the highly populated areas of Kaduna city in the Northern Guinea Savanna region. The wet and dry season weather pattern is experienced in conjunction with rapid urbanization, varied land use, uneven drainage, stagnant water zones, and highly populated communities. This combination of variables might act to enhance, dampen, or even prolong the climatic effects on malaria. However, local quantitative research on this topic is lacking. The current literature in the region addresses only malaria surveillance in Kaduna and risk assessment, or focuses on

other parts of the city but not on Kaduna North LGA (Bajoga et al., 2019; Burga & Mohammed, 2025; Suleiman et al., 2021).

One critical problem is that climate variables and malaria often display pronounced yearly patterns. The strong linear association between wet-season humidity and malaria cases can occur simply because of the similarity of their peak values throughout the year and not because of the impact of humidity variations on malaria cases in the short term. The monthly malaria case numbers are nonnegative integers, which are often highly overdispersed; hence, they cannot be modeled by Gaussian regressions or even simple Poisson regressions. There is also autocorrelation since malaria cases depend on the number of malaria cases, surveillance, and transmission in the previous month. Thus, the importance of considering these aspects of time series analysis and spatiotemporal studies is emphasized in studies that use time series and spatiotemporal analyses to attribute variability in malaria incidence to climate factors (Rubuga et al., 2024; Santos-Vega et al., 2023; Asori et al., 2023).

2 Materials and Methods

2.1 Study Area

The Kaduna North Local Government Area is located in Kaduna State, northern Nigeria, between approximately 10°30'–10°35' N and 7°25'–7°30' E (Figure 1). It forms a densely populated part of the Kaduna metropolis and contains urban and semiurban neighborhoods (Umar et al., 2025). The area lies within northern Guinea Savanna and experiences a tropical wet-and-dry (Aw) climate (Ojonuba et al., 2025). The wet season occurs broadly from May to October under the influence of moist tropical maritime air, whereas November to April is predominantly dry and is influenced by tropical continental air and harmattan (Sankey et al., 2023). The temperature is generally highest toward the end of the dry season and decreases during the core rainy months as the cloud cover and atmospheric moisture increase (Muhammad & Abubakar, 2025).

The area is drained principally by the Kaduna River and associated tributaries. Seasonal streams, low-lying areas, drains and other surface-water environments may provide mosquito breeding opportunities during and following rainfall. Rapid urban development, variable drainage and waste-management conditions, dense housing and heterogeneous land use can further modify local vector habitats (Musa & Abubakar, 2024). These characteristics make Kaduna North suitable for investigating how a strongly seasonal savanna climate interacts with an urban environment to shape malaria occurrence.

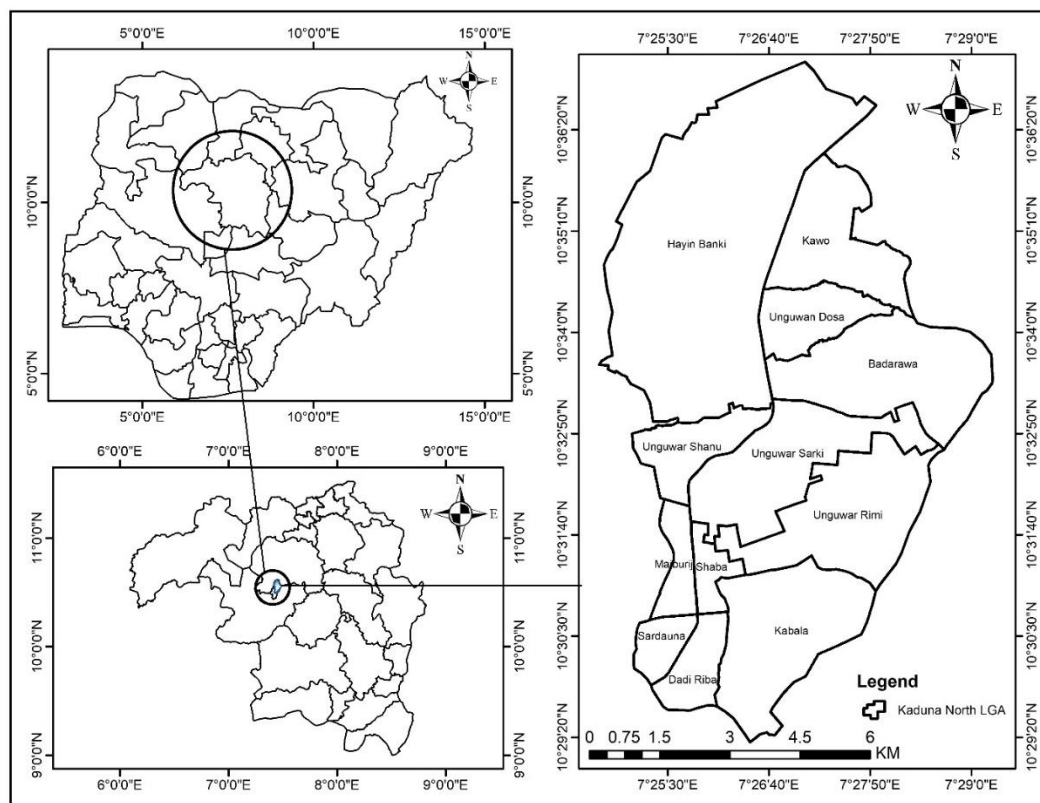


Figure 1: Location of Kaduna North LGA within Kaduna State and Nigeria.

Source: Adapted from Muhammad and Abubakar (2025)

2.2 Study design, data sources and variables

An ecological time series design was employed to examine the relationship between climatic conditions and the incidence of malaria on a monthly basis. The observation period ranged from January 2018 to December 2025, yielding a total of $n = 96$ months of observation data. The month was the time interval of analysis. Since the observation data consisted of aggregated population-level data, the associations found were considered ecological associations rather than individual-level causal relationships.

The climatic data included rainfall (P , mm), relative humidity (RH , %), maximum air temperature (T_{max} , °C), and minimum air temperature (T_{min} , °C). They were all derived from ERA5-Land data provided by the Copernicus Climate Data Store and were aggregated spatially within the Kaduna North LGA area. The malaria data included the number of monthly cases documented by the Health Department of Kaduna North LGA through UNICEF. The malaria cases (Y_t) were regarded as the count outcome variable, while the climatic data constituted the set of explanatory variables. The statistical significance level for two-sided tests was set at 0.05.

2.3 Data preparation and quality control

The climate data and malaria incidence data were chronologically ordered and paired on the basis of year and month. The monthly time series was then tested for

any possible duplication of dates, missing months, missing values, negative values, and implausible observations. The year and month codes were extracted from the date variable. May to October was considered the wet season, whereas November to April was the dry season, to allow general seasonal analysis. However, the calendar month code was maintained in regression adjustments to allow seasonality control at the monthly level.

An unusually low RH level was observed in 2025 relative to that in 2018–2024. The values were retained in the primary analysis because they formed part of the supplied observational record; however, a prespecified sensitivity analysis excluded 2025 and refitted the final model using 2018–2024 data. This permitted the assessment of whether humidity-related inference was disproportionately influenced by the anomalous final year.

2.4 Descriptive statistics and climatology

For each climatic variable and monthly malaria occurrence, the arithmetic mean, sample standard deviation, median, minimum, maximum, and quartiles were calculated. For observations $x_1, x_2, \dots, x_n$, the arithmetic mean was computed as follows:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

The sample standard deviation was calculated as follows:

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

The monthly climatologies were constructed by grouping the observations by calendar month. For variable X , the long-term mean for calendar month m was as follows:

$$\bar{X}_m = \frac{1}{n_m} \sum_{y=1}^{n_m} X_{y,m}$$

where $X_{y,m}$ is the observation in year y and calendar month m , and n_m is the number of valid observations for that month. Annual rainfall was obtained by summing the 12 monthly rainfall totals as follows:

$$P_y = \sum_{m=1}^{12} P_{y,m}$$

The annual RH, Tmax and Tmin were calculated as arithmetic means of their monthly values:

$$\bar{X}_y = \frac{1}{12} \sum_{m=1}^{12} X_{y,m}$$

Annual malaria occurrence was calculated as the sum of monthly reported cases:

$$M_y = \sum_{m=1}^{12} Y_{y,m}$$

2.5 Seasonal Mann–Kendall trend analysis

Because monthly climate and malaria series contain a recurring annual cycle, the Seasonal Mann–Kendall (SMK) test was used as the principal nonparametric trend test (Hirsch & Slack, 1984). The method compares observations belonging to the same calendar month across different years, thereby avoiding direct comparisons of inherently different seasons. For each month m , the Mann–Kendall score was as follows:

$$S_m = \sum_{i=1}^{n_m-1} \sum_{j=i+1}^{n_m} \text{sgn}(x_{j,m} - x_{i,m})$$

$$\text{sgn}(\theta) = \begin{cases} +1, & \text{if } \theta > 0, \\ 0, & \text{if } \theta = 0, \\ -1, & \text{if } \theta < 0. \end{cases}$$

The overall seasonal score was obtained by summing the month-specific statistics:

$$S = \sum_{m=1}^{12} S_m$$

For each calendar month, the variance was corrected for tied observations. If n_m is the number of observations in month m , g_m is the number of tied groups, and t_p is the number of observations in tied group p , then:

$$\text{Var}(S_m) = \frac{n_m(n_m - 1)(2n_m + 5) - \sum_{p=1}^{g_m} t_p(t_p - 1)(2t_p + 5)}{18}$$

Assuming independence among the seasonal blocks, the total variance was as follows:

$$\text{Var}(S) = \sum_{m=1}^{12} \text{Var}(S_m)$$

The standardized normal statistic was calculated with continuity correction as follows:

$$Z = \begin{cases} \frac{S - 1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0, \\ 0, & \text{if } S = 0, \\ \frac{S + 1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0. \end{cases}$$

The two-sided probability value was obtained from the standard normal cumulative distribution function Φ :

$$p = 2[1 - \Phi(|Z|)]$$

A positive significant Z indicated an increasing trend; a negative significant Z indicated a decreasing trend (Abubakar et al., 2025), and the trend magnitude was quantified using the seasonal Sen slope (Haruna et al., 2025). For observations from the same calendar month m in years i and j ($j > i$), the individual slopes were as follows:

$$Q_{ij,m} = \frac{x_{j,m} - x_{i,m}}{j - i}$$

The seasonal Sen slope was the median of all valid within-month pairwise slopes:

$$\hat{\beta}_{\text{Sen}} = \text{median}(Q_{ij,m})$$

Ordinary Mann–Kendall (Kendall, 1975; Mann, 1945) and Sen's slope analyses were also applied to annual summaries as complementary checks. Because only eight annual observations were available, annual trend tests were interpreted as supporting evidence rather than as the principal basis for inference.

2.6 Raw and adjusted lagged climate–malaria associations

Potential delayed climatic effects were examined at lags $k = 0, 1, \dots, 6$ months. For a climatic series X_t and malaria series Y_t , lag k paired climate at month $t - k$ with malaria at month t :

$$r_k = \text{Corr}(X_{t-k}, Y_t), \quad k = 0, 1, \dots, 6$$

Both Pearson product-moment and Spearman rank correlations were computed. The Pearson correlation was as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum_{i=1}^n (x_i - \bar{x})^2][\sum_{i=1}^n (y_i - \bar{y})^2]}}$$

Spearman correlation was calculated as the Pearson correlation between the ranks $R(x_i)$ and $R(y_i)$:

$$\rho_s = \text{Corr}[R(x_i), R(y_i)]$$

Raw lagged correlations can be inflated when climate and malaria share the same annual cycle. Climatic series were therefore adjusted for linear time and calendar-month effects using ordinary least squares:

$$X_t = \alpha_0 + \alpha_1 t + \sum_{m=2}^{12} \gamma_m D_{m,t} + \varepsilon_t$$

where t is linear time, $D_{m,t}$ is a calendar-month dummy variable (one month omitted as the reference category), and ε_t is the season- and trend-adjusted climatic anomaly. Malaria was adjusted using a negative binomial model because preliminary Poisson modelling indicated substantial overdispersion:

$$Y_t \sim \text{NB}(\mu_t, \alpha)$$

$$\log(\mu_t) = \beta_0 + \beta_1 t + \sum_{m=2}^{12} \delta_m D_{m,t}$$

$$\text{Var}(Y_t | \mu_t) = \mu_t + \alpha \mu_t^2$$

Pearson-type residuals from the negative binomial adjustment were calculated as follows:

$$e_t = \frac{Y_t - \hat{\mu}_t}{\sqrt{\hat{\mu}_t + \hat{\alpha} \hat{\mu}_t^2}}$$

Lagged Pearson and Spearman correlations were then recalculated between climatic residuals ε_{t-k} and adjusted malaria residuals. This second-stage analysis was used to determine whether apparent raw associations persisted after the removal of shared calendar seasonality and linear temporal change.

2.7 Multiple-testing control

Because multiple climatic variables and lag combinations were tested, the Benjamini and Hochberg's (1995) false discovery rate (FDR) procedure was applied to reduce false-positive inference. For m hypothesis tests, the observed p -values were ordered as $p(1) \leq p(2) \leq \dots \leq p(m)$. At target FDR $q = 0.05$, the largest rank i satisfying the following criterion was identified:

$$p_{(i)} \leq \frac{i}{m} q$$

All the hypotheses with ranks of 1 through i were considered significant after FDR control. Climatic variables and lags that remained statistically and substantively relevant were considered for multivariable count modeling.

2.8 Count regression, overdispersion and autoregressive modeling

A Poisson generalized linear model was initially fitted as a diagnostic baseline. The Poisson distribution assumes the equality of the conditional mean and variance (Zhang, 2025), $\text{Var}(Y_t | X_t) = E(Y_t | X_t) = \mu_t$. Overdispersion was assessed using the Pearson dispersion statistic:

$$\phi = \frac{\sum_t r_{p,t}^2}{n - p}$$

where $r_{p,t}$ is the Pearson residual, n is the number of observations, and p is the number of estimated parameters. Values substantially greater than 1 were interpreted as evidence that Poisson variance assumptions were violated, motivating negative binomial regression.

Under the NB2 parameterization used in the study, the monthly malaria counts followed a negative binomial distribution with a conditional mean μ_t and a dispersion $\alpha > 0$:

$$Y_t \sim \text{NB}(\mu_t, \alpha), \quad E(Y_t) = \mu_t, \quad \text{Var}(Y_t) = \mu_t + \alpha \mu_t^2$$

The corresponding probability mass function can be written as follows:

$$P(Y_t = y) = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y + 1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_t} \right)^{\alpha^{-1}} \left(\frac{\mu_t}{\alpha^{-1} + \mu_t} \right)^y$$

The candidate climatic predictors were standardized such that the coefficients represented changes associated with a one-standard-deviation increase:

$$Z_{x,t} = \frac{X_t - \bar{X}}{s_x}$$

To account for temporal persistence in malaria, the previous-month malaria count was included after logarithmic transformation:

$$A_t = \ln(Y_{t-1} + 1)$$

The general climate-plus-autoregressive model was specified as follows:

$$\log(\mu_t) = \beta_0 + \beta_1 t + \sum_{m=2}^{12} \delta_m D_{m,t} + \sum_{j=1}^J \beta_j Z_{j,t-k_j} + \theta \ln(Y_{t-1} + 1)$$

where μ_t is the expected monthly malaria occurrence; t represents linear time; $D_{m,t}$ controls calendar-month

seasonality; $Z_{j,t-k_j}$ denotes a standardized climatic predictor j at its selected lag k_j ; and $\ln(Y_{t-1} + 1)$ represents the previous-month malaria burden. Nested specifications were compared so that the incremental contribution of climate could be evaluated relative to temporal trends, seasonality, and autoregressive persistence.

The regression coefficients were exponentiated to obtain the incidence rate ratios (IRRs):

$$\text{IRR}_j = \exp(\beta_j)$$

For coefficient β_j with standard error $\text{SE}(\beta_j)$, the 95% confidence interval on the IRR scale was as follows:

$$95\% \text{ CI}(\text{IRR}_j) = [\exp(\beta_j - 1.96 \text{ SE}(\beta_j)), \exp(\beta_j + 1.96 \text{ SE}(\beta_j))]$$

For standardized climatic predictors, the percentage change in expected malaria occurrence associated with a one-standard-deviation increase was as follows:

$$\% \Delta \mu = 100[\exp(\beta_j) - 1]$$

2.9 Model Comparison and Diagnostics

Competing models were evaluated using the maximized log-likelihood (ℓ), Akaike information criterion (AIC), and Bayesian information criterion (BIC). For k estimated parameters and n observations:

$$\begin{aligned} \text{AIC} &= 2k - 2\ell \\ \text{BIC} &= k \ln(n) - 2\ell \end{aligned}$$

Lower AIC and BIC values indicate better relative fit after penalizing model complexity (Sen & Bradshaw, 2017). Nested models were additionally compared using the likelihood ratio statistic:

$$\text{LR} = 2(\ell_{\text{full}} - \ell_{\text{restricted}})$$

Under the null hypothesis that the additional parameters do not improve fit, the LR was evaluated against a chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the models.

Multicollinearity among the predictors was assessed with the variance inflation factor (VIF). For predictor j :

$$\text{VIF}_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is obtained by regressing predictor j on the remaining predictors. Residual serial dependence was evaluated using the Durbin–Watson statistic:

$$\text{DW} = \frac{\sum_{t=2}^n (e_t - e_{t-1})^2}{\sum_{t=1}^n e_t^2}$$

Values near 2 indicate little first-order residual autocorrelation. The residual lag-1 Pearson correlation was also computed as follows:

$$r_1 = \text{Corr}(e_t, e_{t-1})$$

Residual autocorrelation and partial autocorrelation functions were inspected as additional diagnostics. Negative binomial models were estimated using multiple numerical optimization procedures; only solutions that converged with finite parameter estimates, finite standard errors, and positive dispersion were retained. When more than one valid solution was obtained, the converged solution with the highest log-likelihood was selected.

2.10 Sensitivity Analysis

To test robustness to the exceptional RH observations in 2025, the final autoregressive negative binomial model was refitted after all 2025 observations were excluded. Climatic predictors were re-standardized using only the 2018–2024 subset before model estimation. The direction, magnitude, and statistical significance of the climate coefficients, particularly RH, were compared with those of the full-period model. This analysis was treated as a robustness check rather than a replacement for the primary 2018–2025 analysis.

2.11 Seasonal Variability and STL Decomposition

The malaria seasonal cycle was described using calendar-month means, medians, standard deviations, minima, and maxima. Wet- and dry-season malaria occurrence was compared using Welch's independent-samples t test, which does not require equal group variances. If $\bar{x}_w$ and $\bar{x}_d$ are wet- and dry-season means, s_w^2 and s_d^2 are their sample variances, and n_w and n_d are their sample sizes; then,

$$t = \frac{\bar{x}_w - \bar{x}_d}{\sqrt{\frac{s_w^2}{n_w} + \frac{s_d^2}{n_d}}}$$

The Welch–Satterthwaite degrees of freedom were as follows:

$$v = \frac{\left(\frac{s_w^2}{n_w} + \frac{s_d^2}{n_d}\right)^2}{\frac{(s_w^2/n_w)^2}{n_w - 1} + \frac{(s_d^2/n_d)^2}{n_d - 1}}$$

The Mann–Whitney U test was used as a distribution-free robustness test. The magnitude of the effect of seasonality was quantified with Cohen's d using the pooled standard deviation:

$$\begin{aligned} s_p &= \sqrt{\frac{(n_w - 1)s_w^2 + (n_d - 1)s_d^2}{n_w + n_d - 2}} \\ d &= \frac{\bar{x}_w - \bar{x}_d}{s_p} \end{aligned}$$

The wet-to-dry malaria ratio was calculated as follows:

$$R_{wd} = \frac{\bar{x}_w}{\bar{x}_d}$$

Finally, seasonal-trend decomposition using loess (STL) separated the observed monthly malaria series into trend, seasonal, and remainder components:

$$Y_t = T_t + S_t + R_t$$

where T_t is the smooth trend, S_t is the recurring 12-month seasonal component, and R_t is the remainder. The following variance-based measures of component strength, seasonal strength, and trend strength were calculated as follows:

$$F_{\text{season}} = \max \left[0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(S_t + R_t)} \right]$$

$$F_{\text{trend}} = \max \left[0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(T_t + R_t)} \right]$$

Table 1: Descriptive statistics of climatic variables, 2018–2025

Variable	Mean	SD	Minimum	Median	Maximum
Rainfall (mm)	98.05	118.55	0.00	42.50	424.91
RH (%)	84.47	16.80	19.44	90.97	97.72
Tmax (°C)	32.72	2.64	27.70	32.17	38.60
Tmin (°C)	19.60	2.62	13.60	20.11	24.10

SMK analysis revealed significant changes in rainfall and Tmax. Rainfall significantly decreased ($p=0.0023$), whereas Tmax significantly increased ($Z=3.393$; $p=0.0007$) at an estimated seasonal Sen slope of approximately 0.119 °C year⁻¹. RH ($Z=0.679$; $p=0.4970$) and Tmin ($p=0.6680$)

Values approaching 1 indicate a strong seasonal or trend component. Together, the descriptive seasonal comparisons and STL decomposition were used to distinguish recurring within-year variation from longer-term changes in malaria occurrence.

3 Results

3.1 Climatic patterns and trends

The climatic variables exhibited pronounced monthly variability (Table 1). The mean monthly rainfall was 98.05 mm, and the mean RH was 84.47%; the mean Tmax and Tmin were 32.72 °C and 19.60 °C, respectively. Rainfall increased sharply from April into the wet season and reached a mean monthly maximum of 301.97 mm in August. The RH also peaked in August (96.07%). Tmax was highest in March (36.74 °C) and lowest in August (28.44 °C), whereas Tmin peaked in May (23.31 °C).

did not significantly change. The RH nevertheless displayed an unusual decline in 2025, when the annual mean fell from 90.15% in 2024 to 52.93% (Figure 2).

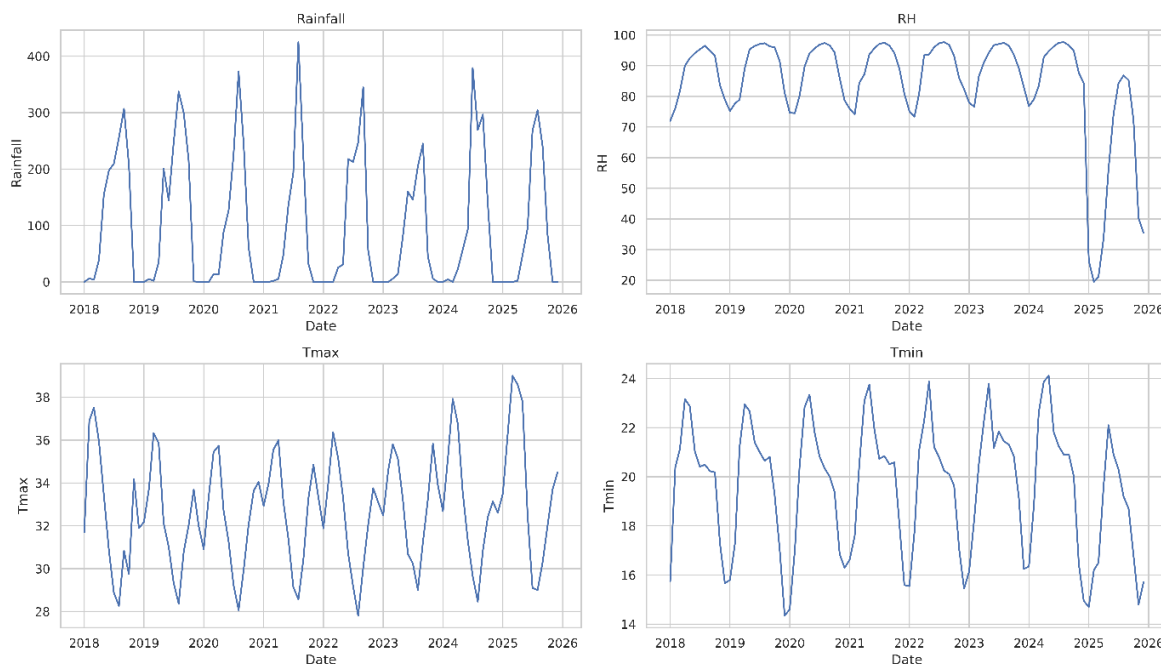


Figure 2: Monthly climate variability in Kaduna North, 2018–2025.

3.2 Temporal pattern and trend of malaria occurrence

The average monthly malaria incidence was 1,761.60 cases, with a median of 1,085.5 and a range of 109–7,216 cases (Figure 3). Annual totals increase from 5,688 cases in 2018 to 48,112 in 2024 before declining to 32,673 in 2025. The SMK test confirmed a highly significant increasing trend after recurring monthly seasonality was accounted for, with a seasonal Sen slope of approximately 324.75 cases year⁻¹. Annual analysis similarly indicated an increasing trend, with a Sen slope of approximately 4,869 cases year⁻¹.

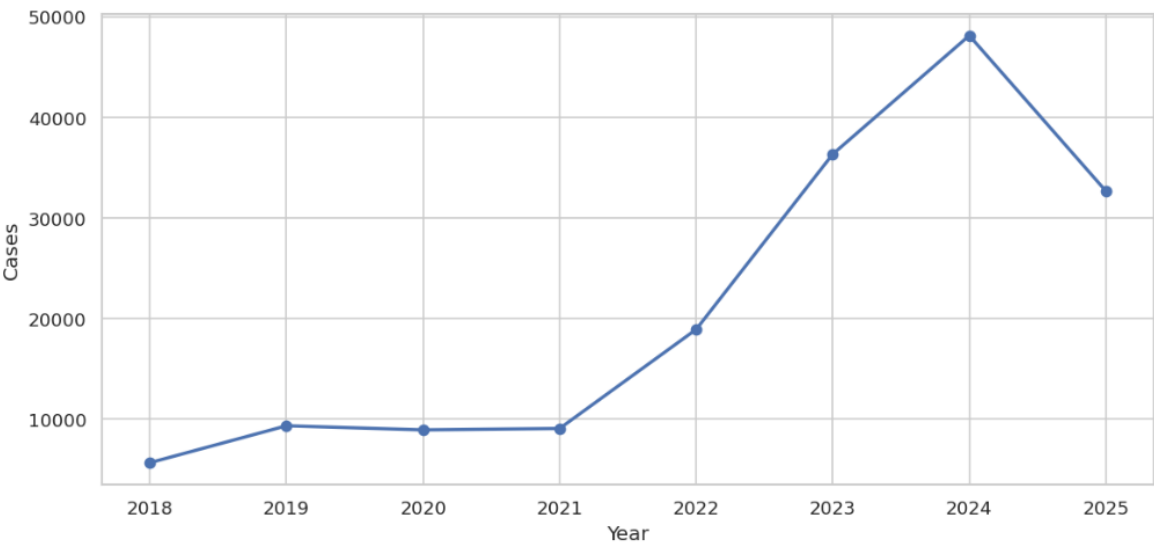


Figure 3: Annual reported malaria cases in Kaduna North, 2018–2025.

3.3 Lagged climate–malaria relationships

Raw lagged correlations revealed an association between malaria and all four climate factors (Figure 4). However, the relationships underwent drastic changes following the removal of common seasonality and temporal trends. Rainfall and Tmax were no longer associated with

malaria after adjustment. RH was positively related to malaria, whereas Tmin was positively related to malaria, although at a two-month lag, both passed the FDR test. This difference reveals that most of the associations found in the raw data for rainfall and Tmax are due to common seasonal cycles.

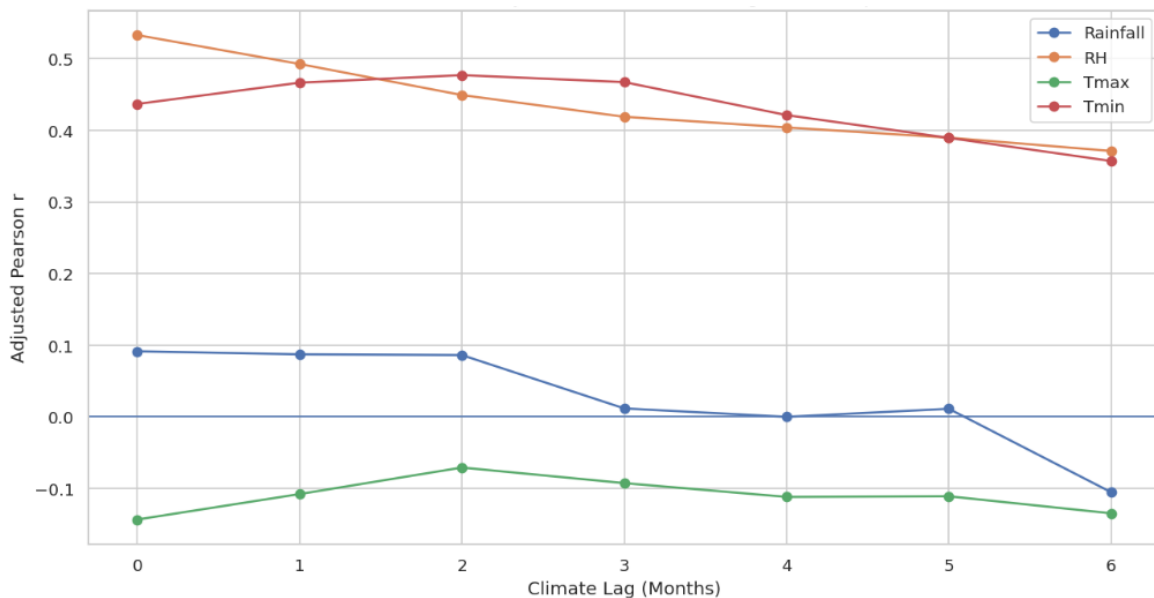


Figure 4: Season- and trend-adjusted climate–malaria relationships across lags of 0–6 months.

3.4 Multivariable climatic predictors and temporal persistence

The Poisson regression at the beginning stage generated a dispersion of approximately 188.38, indicating heavy overdispersion and thus leading to negative binomial

regression (Table 2). With the introduction of seasonality by calendar month, climatic factors, and temporal effects, the model fits improved successively, with the greatest improvement obtained with the addition of malaria in the preceding month.

Table 2: Comparison of negative binomial models

Model	Description	AIC	Interpretation
A	Time	1541.0	Baseline temporal model
B	Time + calendar month	1373.8	Strong improvement after seasonality
C	Time + month + climate	1339.0	Additional improvement from climate
D	Time + month + AR(1)	1183.4	Major improvement after temporal persistence
E	Time + month + climate + AR(1)	1175.5	Best-fitting model

Before adjustment for previous-month malaria, a one-standard-deviation increase in RH was associated with 17.2% higher expected malaria occurrence, whereas a one-standard-deviation increase in Tmin at a two-month lag was associated with 20.2% higher expected occurrence (Table 3). After autoregressive adjustment, the RH effect was attenuated but remained significant in

the full-period model (IRR=1.053, 95% CI 1.018–1.089, $p=0.0024$), which is equivalent to an approximately 5.3% increase in the expected occurrence per standard deviation increase. The association with Tmin was almost completely attenuated (IRR=1.005, 95% CI 0.941–1.073, $p=0.884$). The VIFs were less than 2.2.

Table 3: Climatic effects before and after adjustment for previous-month malaria

Predictor	IRR before AR	p before AR	IRR after AR	95% CI after AR	p after AR	Interpretation
RH lag 0	1.172	—	1.053	1.018–1.089	0.0024	Significant in primary model
Tmin lag 2	1.202	0.025	1.005	0.941–1.073	0.884	Not significant after AR

Autoregressive adjustment also resolved severe residual serial dependence. The Durbin–Watson statistic increased from 0.209 to 1.894, whereas the residual lag-1 correlation decreased from 0.895 to 0.051 ($p=0.628$). However, the RH result was not robust to the sensitivity analysis. When 2025 was excluded, the RH became nonsignificant (IRR=1.025, 95% CI 0.941–1.115; $p=0.574$), and the Tmin remained nonsignificant (IRR=1.002, 95% CI 0.944–1.063; $p=0.946$). RH should therefore be interpreted as the strongest climatic predictor in the

primary model but not as a stable determinant across the full study period.

3.5 Seasonal variability in malaria occurrence

Malaria occurrence showed pronounced monthly seasonality (Figure 5). The mean number of cases increased from 639.1 in January to 2,540.6 in May and 2,961.1 in June, reaching a maximum monthly mean of 3,169.0 in July. The mean occurrence remained high in August (2,954.9) before declining later in the year.

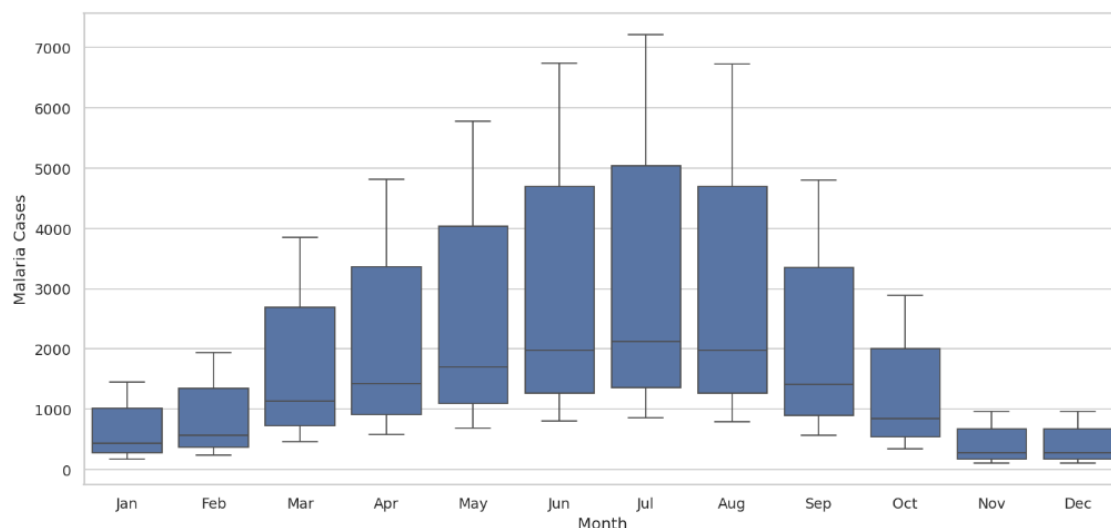


Figure 5: Monthly seasonal distribution of malaria occurrence.

The mean wet-season malaria occurrence was 2,499.75 cases, compared with 1,023.46 cases in the dry season, yielding a wet-to-dry ratio of 2.44 (Figure 6). Both Welch's t-test and the Mann–Whitney U test indicated a statistically significant difference, and Cohen's $d=0.935$

indicated a large wet–dry contrast. STL decomposition yielded a seasonal strength of 0.808 and a trend strength of 0.811, confirming that both recurring seasonality and longer-term change were prominent (Figure 7).

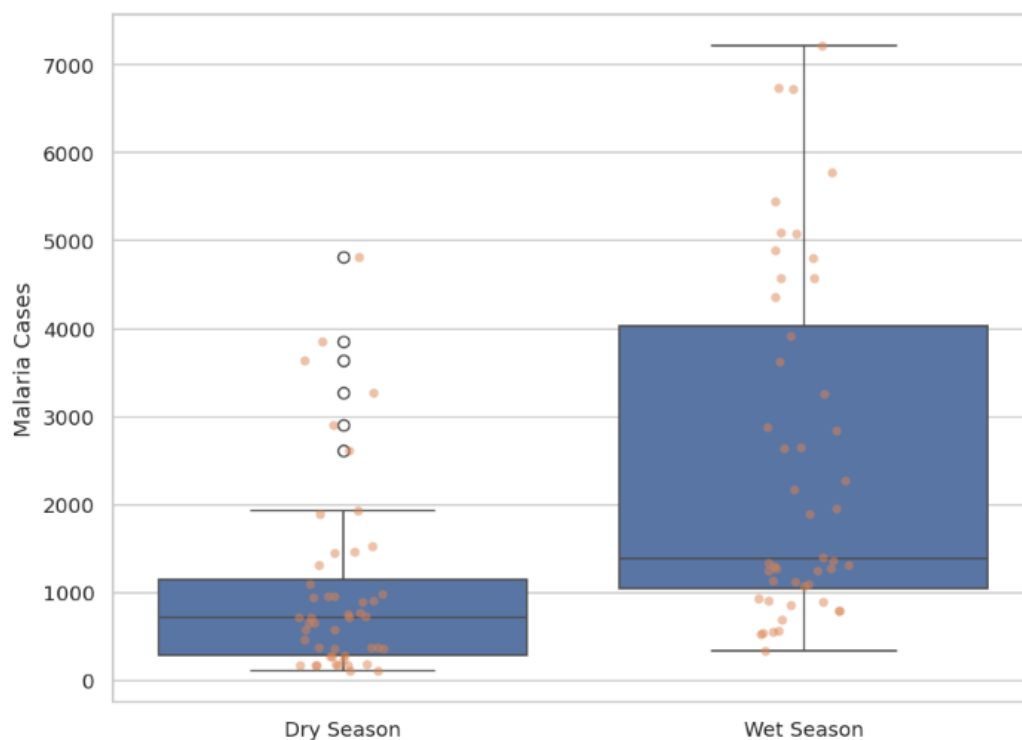


Figure 6: Distribution of reported malaria incidence by wet and dry season.

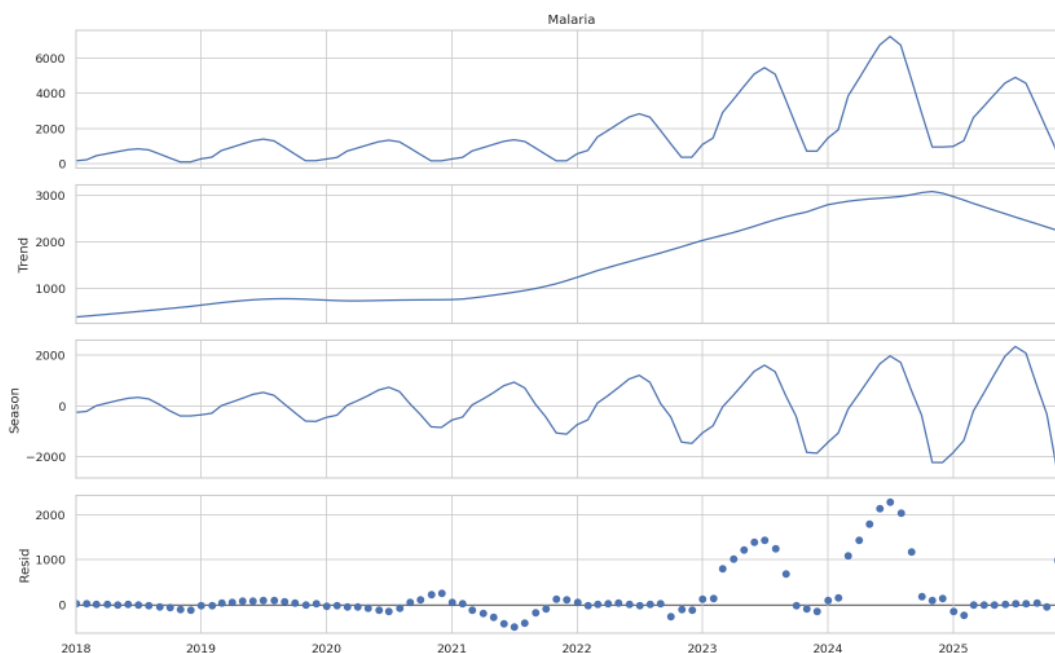


Figure 7: STL decomposition of the monthly malaria series into seasonal, trend and remainder components.

4 Discussion

This study demonstrated that malaria occurrence in Kaduna North is characterized by three overlapping temporal features: a strongly recurring seasonal cycle, a markedly longer-term increase in reported cases, and

substantial short-term persistence from one month to the next. Climatically, rainfall decreased significantly during 2018–2025, whereas T_{max} increased, and RH and T_{min} showed no significant overall trend. The coexistence of a changing climate and increasing malaria does not, however, imply a simple one-to-one climatic explanation.

The eight-year record is relatively short for climate-trend attribution, and malaria reporting is also influenced by surveillance, population, intervention coverage, and healthcare utilization. Nevertheless, the observed climatic changes are consistent with broader evidence that temperature and moisture regimes are changing heterogeneously across Nigeria and Africa rather than uniformly (Ayugi et al., 2024; Balogun et al., 2023; Nooni et al., 2025).

The raw lagged analysis revealed that malaria was positively associated with RH and rainfall and negatively associated with Tmax at several lags. Biologically, these directions are plausible. Rainfall can increase the availability of aquatic breeding habitats, humid conditions can extend adult mosquito survival, and high temperatures can become less favorable once thermal optima are exceeded (Lunde et al., 2013; Mordecai et al., 2013, 2019). Similar climate-malaria associations have been reported in Nigeria and elsewhere in sub-Saharan Africa, although the dominant predictor and lag vary among settings (Bationo et al., 2023; Ekpa et al., 2023; Okunlola & Oyeyemi, 2019; Rubuga et al., 2024; Yamba et al., 2023). The lagged structure observed here is also biologically credible because rainfall-driven habitat formation, larval development, parasite maturation, and clinical presentation occur sequentially rather than instantaneously.

However, importantly, the observed relationships between climate and malaria became much weaker when calendar seasonality and temporal trends were accounted for. That is important to note. Precipitation, relative humidity, and malaria occur in similar parts of the annual cycle, whereas Tmax tends to decrease during the peak season of rainfall. High correlations between climatic factors can thus be easily explained by seasonal synchronization even when there is little evidence of the effects of anomalies in climatic parameters from one month to another. The modified analysis revealed that much of the climate-malaria relationship in Kaduna North could be attributed to seasonal coincidence rather than to a large direct effect of climate factors. This conclusion matches those drawn in the literature, which stresses the importance of accounting for seasonality and time series properties in the estimation of environmental impacts on malaria (Asori et al., 2023; Rubuga et al., 2024; Santos-Vega et al., 2023).

This explains how the multivariate negative binomial regression helps clarify the results. As soon as the trend, calendar month, and previous month's presence of malaria were controlled for, the autoregressive component became highly persistent, and the climatic influence on the independent variables was reduced. This persistence could be because the cases of infection caused in one period are distributed throughout the subsequent

months of data reporting. First, this is because the vector population itself and the environment where vectors live persist from one month to another, and surveillance and health care visits cannot help but have their own temporal dependency. In terms of modeling, this means that without accounting for this, a portion of the temporal pattern would be wrongly attributed to the climate covariates.

Specific care must be taken with respect to the relative humidity. The full series featured a remarkable decrease in RH for the year 2025, and sensitivity analysis revealed that the effect of humidity in inference changed upon excluding that year from the data. Humidity can be mechanistically involved since the survival and behavior of mosquitoes are highly dependent on atmospheric humidity levels, and this has been noted in recent research as an element that contributes to the variation in malaria prevalence in urban environments and seasonality (Nooni et al., 2025; Santos-Vega et al., 2022). However, considering the sensitivity of the humidity factor to inference in the Kaduna North region, it cannot be said that relative humidity serves as a reliable causal predictor based on this study alone.

However, the clear seasonal contrasts, together with the STL analyses, demonstrate that seasonality is still functionally relevant despite the weaker independent impacts of the climatic anomalies that were adjusted for. The prevalence of malaria increased as the rainy season emerged and persisted when precipitation increased further, which is in agreement with the known delay in vector and parasite dynamics throughout sub-Saharan Africa (Bationo et al., 2023; Rubuga et al., 2024; Yamba et al., 2023). Nevertheless, the occurrence of a certain degree of malaria incidence during the dry season suggests that rainfall is not the sole driver of the transmission process. Stable sources of surface water, city drainage, irrigated land, and other human-induced sources of water may support mosquito populations outside the rainy season; indeed, the persistence of malaria transmission due to irrigation has already been recorded elsewhere in Africa (Kibret et al., 2019; Hawaria & Kibret, 2023; Zhou et al., 2022).

The trends in malaria cases must also be understood with respect to nonclimate-related determinants. Urban population growth, urban population density, socioeconomic factors, living standards, mobility, preventive measures, diagnostics, and access to health care could all impact malaria reporting figures. The results for Africa indicate that urbanization and urban population density are determinants of malaria incidence (Kabaria et al., 2017), while socioeconomic factors are still very relevant in terms of exposure and vulnerability (Degarege et al., 2019; Atusingwize et al., 2025). Reporting statistics could also indicate some shifts in detection rates, which

have already been noted in research on Kaduna State surveillance (Bajoga et al., 2019; Ibrahim et al., 2017). Thus, the increasing trend should be interpreted as the growing number of malaria cases reported rather than a direct effect of climate change on malaria incidence.

Overall, these findings neither support nor rule out the climate-malaria relationship in Kaduna North but instead refine the theory. The climate certainly acts as the structure within which the transmission period becomes increasingly favorable, although statistically speaking, the climate is not sufficient to predict the changing trend of malaria after adjusting for seasonality and autocorrelation. This difference is important from a practical point of view because climate variables are best suited for integration into a multidimensional predictive system. A combination of rainfall, humidity, temperature, and previous malaria cases, along with entomological measures, drainage and surface water information, intervention coverage, and health service data, is likely to lead to the formation of a better local surveillance system. This integrated approach is in line with existing research indicating that the climate-malaria link arises from the interplay between climate, vector ecology, environmental modification, and sociodemographic factors (Okunlola & Oyeyemi, 2019; Yamba et al., 2023; Atusingwize et al., 2025).

4.1 Implications for malaria surveillance and control

These results suggest a need for a seasonal and proactive approach to malaria control in Kaduna North. Malaria vector control, environmental sanitization, sensitization of communities, preparations for diagnosis, and provision of commodities should increase during and prior to the wet season and not just when the incidence has reached its peak. Although climatic information can be used for warning systems, this should be done alongside current malaria cases because of the strength of

the autoregressive effect. RH can be considered a secondary predictor, but the sensitivity analysis suggests that this climate predictor should not be used alone as an alert system.

4.2 Limitations

This study had a very short period of analysis, amounting to only eight years, which made it difficult to determine the trends in climate change in the long term and the power of the test for trends each year. The presence of malaria was dependent on recorded malaria cases in health facilities and is likely to be affected by healthcare-seeking. This study did not consider other nonclimatic determinants, such as housing, socioeconomic status, drainage, land usage, intervention coverage, or healthcare accessibility. The unusually high relative humidity values in 2025 strongly affected the RH coefficient.

5 Conclusion

The malaria occurrence in Kaduna North from 2018 to 2025 experienced a notable increasing trend over time, pronounced wet season clustering, and considerable persistence between months. The climate factors also had notable seasonality, which was evident from the decreasing trend of rainfall and the increasing trend of Tmax during the study period. However, the relationships between climate factors and malaria occurrence weakened considerably after controlling for seasonality, temporal trends, and autoregressive disease persistence. RH was significant in the main model for the entire study period but failed the robustness test after 2025 was excluded, whereas the effect of Tmin disappeared after autoregressive control. It can be concluded that there is no evidence that malaria occurrence is influenced by only one climatic factor.

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