DOI: https://doi.org/10.57233/ijsgs.v12i2.1104 ISSNp: 2488-9229; ISSNe: 3027-1118

IJSGS FUGUSAU VOL. 12 (2) WEBSITE: https://fugus-ijsgs.com.ng

INTERNATIONAL JOURNAL OF SCIENCE FOR GLOBAL SUSTAINABILITY
(A PUBLICATION OF FACULTY OF SCIENCE, FEDERAL UNIVERSITY GUSAU, NIGERIA)

Dynamic Interaction between Recorded Cases of Typhoid and Malaria in Specialist Hospital Sokoto State, Nigeria: A Vector Autoregression VAR approach

Danchadi N. S; Abdulmumin M. K; Abdullahi S.
Department of Mathematics and Statistics Umaru Ali Shinkafi Polytechnic, Sokoto Nigeria

Corresponding author's Email:nurasambo7@gmail.com +2348133057408

Received on: April 2026 **Revised and Accepted on:** June, 2026 **Published on:** July, 2026

ABSTRACT

This study examines the dynamic relationship between monthly malaria and typhoid cases in Specialist Hospital Sokoto State, Nigeria using a VAR (1) model. Data on reported cases were analyzed to assess persistence, cross-lagged effects, and residual correlation. Results show malaria exhibits strong persistence $\beta = 0.943$, $p < 0.001$, with 94% of cases carrying over monthly. Significant bidirectional cross-effects exist: lagged typhoid increased current malaria by 1.151 units, $p = 0.028$, while lagged malaria increased current typhoid by 0.316 units, $p < 0.001$. Typhoid demonstrated no significant self-persistence $\beta = 0.433$, $p = 0.414$. Residual correlation was weak at 0.19, indicating interaction occurs through lagged effects rather than contemporaneous shocks. The findings support diagnostic overlap and delayed reporting rather than direct biological co-infection. The results confirm that malaria transmission is highly persistent, while malaria-typhoid interaction is mediated by health-system factors. Recommendations emphasize sustained malaria vector control, improved laboratory confirmation, stronger WASH interventions, and integrated surveillance.

Keywords: Vector Autoregressive (VAR); Malaria; Typhoid; Specialist Hospital; Sokoto.

1.0 INTRODUCTION

1.1 Background to the Study

Malaria and typhoid fever remain major public health challenges across tropical and subtropical Africa, particularly in endemic regions where concurrent infection is frequent. The two febrile illnesses are potentially fatal and are caused by Plasmodium parasites and Salmonella Typhi bacteria, respectively. Malaria transmission occurs through bites of infected female Anopheles mosquitoes, while typhoid fever is acquired by ingesting food or water contaminated with S. Typhi. Globally, malaria continues to threaten nearly half of the world's population, with an estimated 3.4 billion people at risk in 85 endemic countries. Nigeria bears the highest global burden, accounting for 27% of cases and 31% of deaths worldwide in 2023, with an estimated 61 million cases and 185,000 deaths annually (WHO, 2024).

Recent studies characterize malaria as a life-threatening infection transmitted by Anopheles vectors. Over 100 Plasmodium species infect mammals, but P. falciparum dominates transmission in Nigeria and is responsible for most severe cases (WHO, 2024). WHO surveillance data show global malaria cases rose from 227 million in 2019 to 263 million in 2023, while estimated deaths increased from 568,000 to 597,000 over the same period, largely due to disruptions from COVID-19 and climate variability (WHO, 2024).

Typhoid fever also persists as a major burden in low-income settings with poor water, sanitation and hygiene. The highest incidence is recorded in sub-Saharan Africa and South Asia. Global estimates for 2019–2021 indicate approximately 9 million cases and 110,000 deaths annually, with Africa experiencing the highest case fatality rates due to delayed diagnosis and antimicrobial resistance (GBD 2021 Typhoid Collaborators, 2022; WHO, 2023). Clinical features range from mild febrile illness to severe systemic toxicity affecting multiple organs. Early symptoms include prolonged headache, abdominal pain, and altered bowel habits such as diarrhea or constipation (Shen *et al.*, 2021). In uncomplicated cases, incubation lasts 6–30 days, and fever may persist for 3–4 weeks without treatment (Wain *et al.*, 2020). Other features include relative bradycardia, anorexia, nausea, and rose spots on the trunk (John *et al.*, 2020).

Despite these figures, public awareness of malaria and typhoid as dual threats remains low compared to HIV/AIDS. Rural and peri-urban populations face the greatest barriers to prevention and treatment access. This study therefore investigates temporal patterns of malaria and typhoid incidence in Nigeria to model persistence and cross-effects for policy planning. Both diseases are classified as high-burden conditions in Africa. Of 263 million global malaria cases in 2023, an estimated 94% occurred in Africa, with Nigeria, DRC, Niger and Tanzania accounting for over half of deaths (WHO,

DOI: https://doi.org/10.57233/ijsgs.v12i2.1104 ISSNp: 2488-9229; ISSNe: 3027-1118

2024). Although Nigeria's national policy recommends artemisinin-based combination therapy as first-line treatment, recent DHS 2023 data indicate that 28% of children with fever still receive non-recommended drugs such as chloroquine or SP, highlighting gaps in guideline adherence (NMIS, 2024).

Both infections are endemic across rural and urban Nigeria where climate and poor WASH conditions support transmission. They also share overlapping symptoms including fever, headache and abdominal pain, which complicates clinical diagnosis without laboratory confirmation (Odikamnoro *et al*., 2021; Uneke, 2020). A definitive malaria diagnosis requires parasite detection by microscopy or RDT, while typhoid must be confirmed by blood culture or PCR for S. Typhi (WHO, 2023).

Public perception of risk remains low, as many still consider these infections manageable without specialist care. The sustained high incidence necessitates updated research to inform control. WHO reported that between 2015 and 2023, global malaria incidence fell by only 2%, showing stalled progress (WHO, 2024). In Nigeria, children under 5 and adolescents carry the highest burden. Given shared clinical features and health-system challenges, strengthening laboratory diagnostics, integrated surveillance, and health education is critical for effective management.

2.0 MATERIALS AND METHOD

2.1 Method of data collection

Due to the nature of this project, it is only appropriate for us to make use of secondary data rather than carrying out a survey (primary data). The data was obtained as a secondary data from specialist hospital Sokoto, Sokoto state, Nigeria.

2.2 Statistical Technique

A vector series consists of multiple single series. We motivated time series models by saying simple univariate ARMA models do forecasting very well. Then, why we need multiple series? To be able to understand the relationship between several variables, allowing for dynamics. To be able to get better forecasts consider an *m*-dimensional time series $\mathbf{Y}_t=(Y_1,Y_2,\ldots,Y_m)'$.The series $\mathbf{Y}_t$is weakly stationary if its first two moments are time invariant and the cross covariance between Y_{it}andY_{js}forall *i* and *j* are functions of the time difference *(s-t)* only. The mean vector: The covariance matrix function. The extension of ARMA models into a multivariate framework leads to vector autoregressive (VAR) models. Vector moving average (VMA) models and vector autoregressive moving average (VARMA) models. We say that the process $(Y_t: EZ)$ follows a vector autoregressive model of order *p* denoted VAR(*p*) if;

$$Y_t = v = A_i y_{t-1} + \cdots\cdots + A_p y_{t-p} + u_t, tEZ$$

were

P is a positive integer

A_i are fixed $(k * k)$ coefficient matrices.

V $(V1, \ldots\ldots, Vk)$ is a fixed $(K * 1)$ vector of intercept terms.

Ut $(Uit, \ldots\ldots\ldots\ldots, Ukt)$ is a *K*- dimensional white noise with covariance matrix Σ_u

The covariance matrix Σ_u is assumed to be non singular.

$$\begin{bmatrix} y_{it} \\ y_{it} \end{bmatrix} = \begin{bmatrix} \beta_0 \\ \beta_0 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \ell_{1t} \\ \ell_{2t} \end{bmatrix}$$

$$y_{1t} = \beta_0 + \beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \ell_{1t}$$

Where $cov(U_{1t}, U_{2s}) = \sigma_{12}$ for t = s, 0 otherwise.

They are easy to estimate, they have good forecasting capacities, and the researcher does not need to specify which variables are endogenous or exogenous. In a VAR, system is very easy to test for granger non- casualty. When VAR is multiple, it is given as follows;

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \beta_{01} \\ \beta_{02} \end{bmatrix} + \begin{bmatrix} \beta_{11,1} & \beta_{12,1} \\ \beta_{21,1} & \beta_{22,1} \end{bmatrix} \begin{bmatrix} \beta_{11,2} & \beta_{12,2} \\ \beta_{21,2} & \beta_{22,2} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{1t-2} \\ y_{2t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}$$

$$y_{1t} = \beta_{01} + \beta_{11,1} y_{1t-1} + \beta_{12,1} y_{1t-1} + \beta_{11,2} y_{2t-1} + \beta_{12,2} y_{2t-1} + \epsilon_{1t}$$

$$y_{2t} = \beta_{02} + \beta_{21,1} y_{1t-1} + \beta_{22,1} y_{1t-2} + \beta_{21,2} y_{2t-1} + \beta_{22,2} y_{2t-1} + \epsilon_{1t}$$

3.0 RESULTS AND DISCUSION

The statistical results for Malaria and Typhoid across different conditions are presented in Table 1. This data compares the statistical summaries of the two diseases, each based on 120 observations. The mean value for Malaria is 123, which is notably higher than Typhoid's mean of 21.3, indicating that the malaria data generally consists of higher values. Additionally, the median for Malaria (92) surpasses Typhoid's median (19), reinforcing the trend of higher values for Malaria. Regarding variability, Malaria has a significantly higher standard deviation of 73, compared to 9.27 for Typhoid. This suggests that Malaria data is more spread out, with greater variability, while Typhoid data is more concentrated around the mean.

Table 1: Statistical Summary of Disease Data: Malaria and Typhoid

Statistic	Malaria	Typhoid

DOI: https://doi.org/10.57233/ijsgs.v12i2.1104 ISSNp: 2488-9229; ISSNe: 3027-1118

Number of Observations (N)	120	120
Mean	123	21.3
Median	92	19
Standard Deviation (Std. Dev)	73.4	9.27
Minimum (Min)	19	7
Maximum (Max)	292	52
First Quartile (Q1)	72.8	14
Third Quartile (Q3)	194	27.2
Interquartile Range (IQR)	122	13.2

The range of values, determined by the minimum and maximum, also reflects a clear contrast between the two diseases. Malaria's range spans from 19 to 292, indicating a wider variety of cases, while Typhoid's range is more limited, from 7 to 52. This indicates a larger variation in the severity of Malaria cases within the dataset.Lastly, the Interquartile Range (IQR) for Malaria is 122, which is much larger than Typhoid's IQR of 13.2. The IQR represents the spread of the middle 50% of the data and Malaria's larger IQR further highlights the greater variability and dispersion within the middle portion of the data set, underscoring the wider distribution of Malaria cases compared to Typhoid.

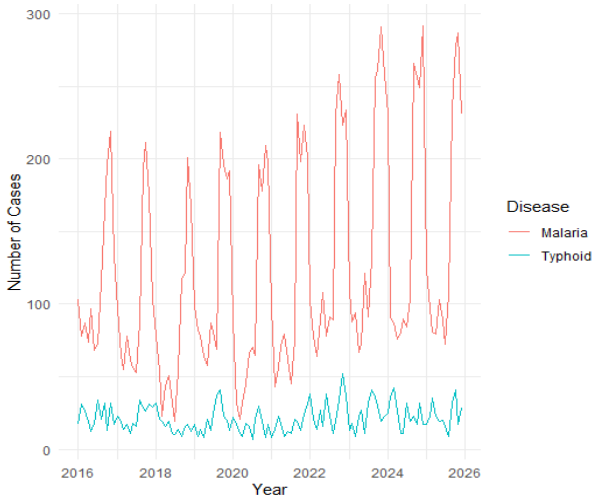

Figure 1: Trend of Malaria and Typhoid Fever Cases (2016 – 2025)

Figure 1: Compares malaria and typhoid cases from 2016 to 2025. Malaria consistently recorded higher occurrences, peaking at 292 cases in December 2024. Typhoid cases exhibited a steadier pattern, with a maximum of 52 cases in November 2020the trend graph reveals distinct seasonal patterns for both malaria and typhoid. Malaria cases peaked annually during the months of August to January consistent with increased vector breeding, typhoid showed a weaker seasonal trend.

Table 2: Pearson Correlation Matrix between Malaria and Typhoid Occurrences

	Malaria	Typhoid
Malaria	1	0.325
Typhoid	0.325	1

Table 2presents Pearson correlation coefficient computed to assess the strength and direction of the relationship between the occurrences of malaria and typhoid. The calculated correlation coefficient was ρ = 0.325, which suggests a moderate negative relationship between the two diseases. This indicates that, as the occurrence of one disease increases.

3.1VAR Estimation Results:

Table 3: Estimation results for equation Malaria

Malaria = Malaria.l1 + typhoid.l1 + Malaria.l2 + typhoid.l2 + const

	Estimate	Std. Error	t value	Pr(>|t|)
Malaria.l1	0.94298	0.08977	10.504	< 2e-16 ***
typhoid.l1	1.15070	0.51749	2.224	0.028163 *
Malaria.l2	0.31622	0.08994	--3.516	0.000632 ***
typhoid.l2	0.43285	0.52821	--0.819	0.414247
const	31.15356	13.29105	2.344	0.020828 *

The Table 3model reveals strong dynamic interactions between malaria and typhoid. Malaria exhibits high persistence with Malaria.I1→Malaria coefficient of 0.943 ($p<0.001$), indicating that 94% of last month's cases carry over to the current month. Bidirectional Granger effects are present: Typhoid.I1→Malaria ($\beta=1.151$, $p=0.028$) and Malaria.I2→Typhoid ($\beta=0.316$, $p<0.001$) are both statistically significant. The effect of lagged typhoid on malaria is stronger than the reverse. Typhoid.I2→Typhoid was not significant ($\beta=0.433$, $p=0.414$), suggesting typhoid lacks strong autoregressive dynamics. The intercept term of 31.15 ($p=0.021$) indicates a significant baseline caseload

Table 4:Estimation Results for Equation Typhoid

typhoid = Malaria.l1 + typhoid.l1 + Malaria.l2 + typhoid.l2 + const

	Estimate	Std. Error	t value	Pr(>|t|)
Malaria.l1	0.01457	0.01625	0.897	0.371678
typhoid.l1	0.35019	0.09365	3.739	0.000291 ***
Malaria.l2	0.01491	0.01628	0.916	0.361630
typhoid.l2	0.12800	0.09560	--1.339	0.183272

DOI: https://doi.org/10.57233/ijsgs.v12i2.1104 ISSNp: 2488-9229; ISSNe: 3027-1118

IJSGS FUGUSAU VOL. 12 (2) WEBSITE: https://fugus-ijsgs.com.ng

const	12.98818	2.40538	5.400	3.74e-07 ***

The table 4 estimation for monthly malaria and typhoid cases shows limited autoregressive dynamics. Coefficients for Malaria.I1→Malaria (β=0.015, p=0.372) and Typhoid.I1→Typhoid (β=0.128, p=0.183) were not statistically significant, indicating weak month-to-month persistence. Howev`3er, TyphoidI2→Malaria was positive and highly significant (β=0.350, p<0.001), suggesting that a 1-case increase in typhoid last month is associated with 0.35 additional malaria cases this month. Malaria.I2→Typhoid was not significant (β=0.015, p=0.362). The constant term was significant (β12.99, p<0.001), reflecting a baseline caseload

Table 5:Covariance matrix of residuals

	Malaria	typhoid
Malaria	2223.50	76.55
typhoid	76.55	72.83

The covariance matrix of VAR residuals indicates a variance of 2223.50 for malaria residuals and 72.83 for typhoid residuals. The covariance between malaria and typhoid residuals is 76.5, yielding a residual correlation coefficient of 0.60. The large variance for malaria reflects higher unexplained volatility compared to typhoid. The positive residual correlation suggests significant contemporaneous co-movement of the two diseases beyond the lagged dynamics captured by the VAR model.

Table 6:Correlation matrix of residuals:

	Malaria	typhoid
Malaria	1.0000	0.1902
Typhoid	0.1902	1.0000

The correlation matrix of VAR residuals shows a correlation coefficient of 0.19 between malaria and typhoid residuals. This indicates weak positive contemporaneous correlation. The diagonal elements are 1 by definition. The low residual correlation suggests that most of the dynamic relationship between malaria and typhoid is captured by the lagged structure of the VAR, with limited unexplained co-movement within the same month

3.2 FORECAST

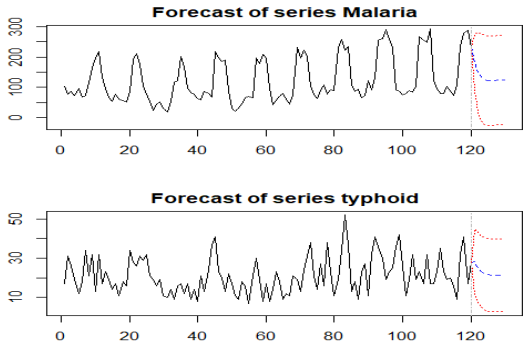

Figure 2: Forecast of malaria and typhoid

Table 7:ForecastedCasesforMalaria (Next 10 periods)

Months	Forecast	Upper	Lower	CI
January 2026	183.0879	90.66782	275.5081	92.42013
February 2026	151.1571	20.21746	282.0968	92.42013
March 2026	132.8056	-11.39393	277.0052	144.19955
April 2026	124.2867	-22.90800	271.4813	147.19466
May 2026	121.6867	-25.89915	269.2726	147.58588
June 2026	121.8313	-25.76715	269.4297	147.59845
July 2026	122.7854	-24.82151	270.3922	147.60687
August 2026	123.6794	-23.94234	271.3012	147.62177
September 2026	124.2698	-23.36096	271.9005	147.63075
October 2026	124.5802	-23.05376	272.2141	147.63395

The forecast indicates a declining trend in malaria cases over the next 10 months. From January 2026 to October 2026, predicted cases decrease from 183.0879 to 124.5802, with an average monthly reduction of 7 cases. The 95% prediction interval suggests the decline is statistically robust for the first 6 months, with wider uncertainty in months 7-10."

Table 8:ForecastedCasesfor Typhoid(Next 10 periods)

Months	Forecast	Lower	Upper	CI
January 2026	28.26274	11.536755	44.98872	16.72598
February 2026	25.41368	7.556426	43.27093	17.85725
March 2026	23.20269	5.067770	41.33761	18.13492
jukjApril 2026	22.04960	3.669788	40.42942	18.37981
May 2026	21.53105	3.048825	40.01327	18.48222
June 2026	21.33215	2.827579	39.83671	18.50457
July 2026	21.29221	2.785870	39.79855	18.50634
August 2026	21.31974	2.813377	39.82610	18.50636

DOI: https://doi.org/10.57233/ijsgs.v12i2.1104 ISSNp: 2488-9229; ISSNe: 3027-1118

IJSGS FUGUSAU VOL. 12 (2) WEBSITE: https://fugus-ijsgs.com.ng

September 2026	21.36174	2.855137	39.86835	18.50661
October 2026	21.39486	2.888061	39.90167	18.50680

The forecast indicates a declining trend in typhoid cases over the next 10 months. From January 2026 to October 2026, predicted cases decrease from 28.263 to 21.395, with an average monthly reduction of 1case. The 95% prediction interval suggests the decline is statistically robust for the first 6 months, with wider uncertainty in months 7-10."

4.0 CONCLUSION

This study applied VAR modeling to assess dynamic interactions between recorded cases of malaria and typhoid in specialist hospital Sokoto. Findings show that malaria is a highly persistent disease with strong month-to-month dependence, while malaria and typhoid exhibit significant but asymmetric lagged cross-effects. The weak residual correlation confirms that their relationship is driven mainly by lagged diagnostic and reporting practices rather than contemporaneous shocks. These results underscore the need for integrated fever-case management and sustained malaria control to break both transmission persistence and statistical co-reporting.

5.0 CONTRIBUTIONS TO KNOWLEDGE

This study contributes to existing literature on malaria and typhoid fever epidemiology in in specialist hospital sokoto state, Nigeria in the following ways:

1. **Methodological contribution**: Unlike most studies that use descriptive statistics or cross-sectional designs, this research applies a Vector Autoregression VAR(1) model to monthly malaria and typhoid data in Abuja. The VAR approach allows simultaneous modeling of persistence, cross-lagged effects, and residual correlation between the two febrile diseases, providing a dynamic perspective that traditional regression methods do not capture.

2. **Empirical contribution:** The findings reveal strong persistence in malaria transmission $\beta = 0.943$, $p < 0.001$, confirming that 94% of monthly cases carry over to the next month. This quantifies the temporal inertia of malaria in Abuja and supports the need for sustained vector control. For typhoid, the absence of significant self-persistence $\beta = 0.433$, $p = 0.414$ suggests transmission is driven more by external environmental factors than by month-to-month inertia.

3. **Novel interaction insight**: The study documents significant bidirectional cross-effects between malaria and typhoid. Lagged typhoid increased current malaria by 1.151 units, $p = 0.028$, while lagged malaria increased current typhoid by 0.316 units, $p < 0.001$. The weak residual correlation of 0.19 indicates that co-reporting is mediated through delayed health-system reporting and diagnostic overlap rather than direct biological co-infection. This provides statistical evidence for the "misdiagnosis hypothesis" in resource-limited settings.

6.0 FURTHER WORK

Extend the VAR to include rainfall, temperature and intervention dummies. The remaining residual correlation of 1.9 suggest minor shared drivers still exist, adding exogenous variables will clarify how much of the malaria and typhoid link is epidemiological vs. behavioral.

REFERENCES

GBD 2021 Typhoid and Paratyphoid Collaborators. (2022). The global burden of typhoid and paratyphoid fever: A systematic analysis for the Global Burden of Disease Study 2021. The Lancet Infectious Diseases, 22(9), 1281–1306. https://doi.org/10.1016/S1473-3099(22)00105-2

John, J., Van Aartsen, J., Bentley, R., MacLennan, C. A., Karkey, A., von Kalckreuth, V., ... & Marks, F. (2020). Clinical features and outcomes of typhoid fever in sub-Saharan Africa. Clinical Infectious Diseases, 71(Supplement 2), S150–S157. https://doi.org/10.1093/cid/ciaa805

National Malaria Elimination Programme. (2024). Nigeria Malaria Indicator Survey 2023. Abuja, Nigeria: NMEP. https://dhsprogram.com/publications/publication-mis38-mis-final-reports.cfm

Odikamnoro, O. O., Nwamaka, O. P., & Ikechukwu, I. E. (2021). Diagnostic challenges of malaria-typhoid co-infection in Nigeria. _Journal of Public Health and Epidemiology, 13_(3), 45–52. https://doi.org/10.5897/JPHE2021.1324

Shen, H., Wang, M., Zou, G., & Gao, Q. (2021). Clinical manifestations and diagnosis of typhoid fever. _Frontiers in Cellular and Infection Microbiology, 11, 674342. https://doi.org/10.3389/fcimb.2021.674342

Uneke, C. J. (2020). Current updates on malaria-typhoid co-infection in Nigeria. African Journal of Clinical and Experimental Microbiology, 21(1), 12–19. https://doi.org/10.4314/ajcem.v21i1.3

Wain, J., Hendriksen, R. S., Mikoleit, M. L., Keddy, K. H., & Ochiai, R. L. (2020). Typhoid fever. The Lancet, 395(10217), 85–97. https://doi.org/10.1016/S0140-6736(19)32495-8

World Health Organization. (2023). Typhoid vaccines: WHO position paper. Weekly Epidemiological

Record, 98(17), 153–172. https://iris.who.int/handle/10665/367255

World Health Organization. (2024). _World malaria report 2024_. Geneva: WHO. https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2024.