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AN ARMA MODEL FOR PREDICTING THE MORBIDITY INCIDENCE OF TYPHOID FEVER IN PLATEAU STATE, NIGERIA

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ABSTRACT

Background: Reliable forecasts of typhoid fever cases help health authorities plan diagnostics, antibiotics and prevention and detect unusual increases early. The only forecasting model available for Plateau State, Nigeria, an ARMA(2,2) model fitted to data up to mid-2023, was selected without a white-noise benchmark or out-of-sample validation. This study re-examined the Box–Jenkins modelling of the state's typhoid surveillance series and produced validated forecasts to December 2027.

Methods: Monthly counts of serologically confirmed typhoid cases reported to the Epidemiology Unit of the Plateau State Ministry of Health from January 2007 to December 2025 (228 months; 240,659 cases) were log-transformed and examined for trend, seasonality (Kruskal–Wallis test), changes in variability (Levene's test), autocorrelation (Ljung–Box test) and unit roots (Ng–Perron and augmented Dickey–Fuller tests). All 25 ARMA(p, q) models with $p, q \leq 4$ were estimated on a common sample and compared using the Akaike, Schwarz and Hannan–Quinn criteria and likelihood-ratio tests. Forecast accuracy was evaluated on a 12-month hold-out period (2025) against a seasonal naïve benchmark.

Results: The series was stationary, I(0), with no significant trend ($p = 0.746$), seasonality ($p = 0.141$) or autocorrelation up to lag 24 (all Ljung–Box $p \geq 0.195$). All three criteria selected ARMA(0,0), $\ln Y_t = 6.9595 + \varepsilon_t$. The ARMA(2,2) model explained 2.7% of the variation, did not improve significantly on ARMA(0,0) (LR $\chi^2(4) = 6.33$, $p = 0.176$) and had nearly cancelling autoregressive and moving-average roots. On the hold-out year, ARMA(0,0) achieved a mean absolute percentage error of 6.37%, against 9.22% for the seasonal naïve benchmark, with no significant bias (paired $t = 0.036$, $p = 0.972$). A forecast made from data to June 2023 contained 28 of the 30 subsequently observed months within its 95% prediction

interval. Month-to-month variability was significantly lower in 2019–2022 than before or after (Levene $p < 0.001$), while the mean was unchanged. The model forecasts about 1,053 cases per month (95% prediction interval 922–1,203) for 2026–2027.

Conclusion: Typhoid morbidity in Plateau State is high and stable, with no evidence of decline. A parsimonious constant-mean model forecasts it as well as more complex models, and its upper prediction limit offers a practical alert threshold for routine surveillance.

KEYWORDS: Typhoid Fever; Arma Model; Box–Jenkins methodology; model parsimony; forecast validation; disease surveillance; Nigeria.

1. INTRODUCTION

Typhoid fever is a systemic infection caused by *Salmonella enterica* serovar Typhi. Humans are its only natural host, and it spreads mainly through food and water contaminated with the faeces of infected people or carriers (Meiring et al., 2023). Without effective treatment, complications such as intestinal perforation and gastrointestinal bleeding can be fatal; a recent global meta-analysis estimated a pooled case-fatality ratio of 2.1% (Murthy et al., 2025). Limited hygiene, unimproved sanitation, surface-water sources and street food all raise the risk of infection (Kim et al., 2023; Okyere et al., 2025). The World Health Organization estimates about 9 million cases and 110,000 deaths each year (WHO, 2023). Although the global age-standardised incidence of typhoid and paratyphoid fevers fell from 461.3 to 127.8 per 100,000 between 1990 and 2021 (Shi & You, 2025), incidence in sub-Saharan Africa remains high, particularly in Western and Eastern Africa and among children aged 5 to 14 years (Kim et al., 2024). The Severe Typhoid in Africa programme, which included a Nigerian site, confirmed a high population-based incidence across six African countries (Marks et al., 2024).

Nigeria is endemic for typhoid. Most invasive *Salmonella* infections sequenced in southwestern Nigeria were caused by a multidrug-resistant lineage of *S.* Typhi (Ikhimiukor et al., 2022), and typhoidal isolates from febrile patients in Lafia, Nasarawa State, which borders Plateau State, were highly resistant to first-line antibiotics (Ngolo et al., 2025). Diagnosis is a further challenge, because many facilities rely on the Widal test, whose average sensitivity and specificity in recent studies were only about 63% and 73% (Tegene & Eshetie, 2025). Typhoid conjugate vaccine has not yet been introduced nationally (Ashikeni et al., 2026). In this setting, state health authorities need reliable forecasts of the number of cases to expect each month, both to plan resources and to recognise unusual increases.

The Box–Jenkins autoregressive moving average (ARMA) model and its integrated (ARIMA) and seasonal (SARIMA) extensions are widely used for this purpose, because they need only the series itself, follow a well-established procedure for building and checking a model, and produce forecasts with measurable uncertainty (Hyndman & Athanasopoulos, 2021; Shumway & Stoffer, 2025). They have recently been applied to typhoid in Ghana (Baffoe et al., 2026), Benue State, Nigeria (Jighjigh et al., 2025) and Delhi, India (Tripathi et al., 2026), to foodborne diseases in China (Xian et al., 2023; Du et al., 2025), and to mpox (Bakare et al., 2025) and Lassa fever (Musa et al., 2024) in Nigeria. Most such studies select a model from the sample autocorrelation functions and information criteria. Fewer compare the selected model with a simple benchmark or test it on data withheld from fitting, although these checks guard against over-fitting and are standard in forecasting practice (Hyndman & Athanasopoulos, 2021); Jighjigh et al. (2025) and Du et al. (2025) are notable exceptions.

For Plateau State, a previous unpublished analysis (Amua, 2024) applied the Box–Jenkins procedure to monthly confirmed typhoid cases from January 2007 to June 2023 and selected an ARMA(2,2) model, with a reported R^2 of 75.75%, an implied eight-month cycle and a forecast decline to June 2025. However, the candidate set excluded ARMA(0,0), the natural benchmark when a series shows no significant autocorrelation; the forecasts were checked against observations from within the fitting period; and the forecast values themselves were essentially flat. Recent published studies of typhoid in Plateau State are otherwise scarce.

This study therefore re-examines ARMA modelling of the Plateau State typhoid series, extended by 30 months to December 2025. Its objectives were to (i) describe the trend, seasonality, variability and stationarity of the series; (ii) identify, estimate and compare ARMA(p, q) models with p, $q \leq 4$, including the white-noise benchmark; (iii) evaluate out-of-sample forecast accuracy over a 12-month hold-out period; and (iv) forecast monthly cases, with 95% prediction intervals, from January 2026 to December 2027.

2. MATERIALS AND METHODS

2.1 Study area and data

Plateau State lies in the north-central geopolitical zone of Nigeria. Its capital is Jos, and it has 17 local government areas. Most of its population lives in rural farming communities, many of which rely on wells, streams and other unimproved water sources. The study used secondary data: monthly counts of serologically confirmed typhoid fever cases in the state from January 2007 to December 2025 (228 months; 240,659 cases), obtained from the Epidemiology Unit of the Plateau State Ministry of Health, Jos. The first 198 months are the

series analysed by Amua (2024); the remaining 30 months (July 2023 to December 2025) were obtained later from the same source. December 2025 was the most recent month available at the time of data collection. The full series is given in Supplementary Table S1.

2.2 Transformation and exploratory analysis

The series was transformed to natural logarithms,

$$y_t = \ln Y_t, \qquad t = 1,2,\ldots,228 \qquad (1)$$

where Y_t is the number of confirmed cases in month t. The transformation makes effects proportional and keeps back-transformed forecasts and prediction limits positive. Normality was assessed with the Jarque–Bera statistic (Uyanto, 2022),

$$JB = \frac{n}{6}\left[\hat{S}^2 + \frac{(\hat{K}-3)^2}{4}\right] \sim \chi^2_2 \qquad (2)$$

where $\hat{S}$ and $\hat{K}$ are the sample skewness and kurtosis. A linear trend was tested by regressing y_t on t. Differences in variability between three periods (January 2007–December 2018, January 2019–December 2022 and January 2023–December 2025) were tested with Levene's test, and differences in means with one-way analysis of variance. Seasonality was tested by comparing the log series across the twelve calendar months using one-way analysis of variance and the Kruskal–Wallis statistic,

$$H = \frac{12}{N(N+1)}\sum_{j=1}^{12}\frac{R_j^2}{n_j} - 3(N+1) \qquad (3)$$

where R_j is the rank sum and n_j the number of observations in month j, and $N = 228$; under the null hypothesis, H is approximately χ^2 with 11 degrees of freedom.

The sample autocorrelation at lag k is

$$\hat{\rho}_k = \frac{\sum_{t=k+1}^{n}(y_t-\bar{y})\,(y_{t-k}-\bar{y})}{\sum_{t=1}^{n}(y_t-\bar{y})^2} \qquad (4)$$

and the partial autocorrelations were obtained by the Durbin–Levinson recursion. Under the white-noise hypothesis both are approximately N(0, 1/n), giving 95% limits of $\pm 1.96/\sqrt{n}$. The joint significance of the first h autocorrelations was tested with the Ljung–Box statistic,

$$Q(h) = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \sim \chi^2_{h-m} \qquad (5)$$

where m is the number of estimated ARMA parameters ($m = 0$ for the raw series).

2.3 Unit root tests

The order of integration was determined with the Ng–Perron modified unit root test, which retains good size and power in series of moderate length (Wang et al., 2024). The series is first detrended by generalised least squares (GLS) using quasi-differencing with $\bar{\alpha} = 1 + \bar{c}/T$, where $\bar{c} = -7$ for the intercept-only case and $\bar{c} = -13.5$ when a linear trend is included. With y_t^d the GLS-detrended series, $\kappa = T^{-2}\sum_{t=2}^{T}\left(y_{t-1}^d\right)^2$ and s_{AR}^2 an autoregressive spectral estimate of the long-run variance, the test statistics are

$$MZ_\alpha = \frac{T^{-1}\left(y_T^d\right)^2 - s_{AR}^2}{2\kappa}, \qquad MSB = \left(\frac{\kappa}{s_{AR}^2}\right)^{1/2}, \qquad MZ_t = MZ_\alpha \times MSB \qquad (6)$$

Together with the modified point-optimal statistic MP_T. The unit-root null hypothesis is rejected when the statistics are smaller than their asymptotic critical values; the spectral lag length was chosen by the Schwarz criterion. As a check, the augmented Dickey–Fuller (ADF) test was applied to

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t \qquad (7)$$

with and without the trend term, testing H_0: $\gamma = 0$ (Shumway & Stoffer, 2025).

2.4 Model specification, estimation and selection

The ARMA(p, q) model for the stationary log series is

$$\phi(L)(y_t - \mu) = \theta(L)\varepsilon_t, \qquad \phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i, \qquad \theta(L) = 1 + \sum_{j=1}^{q} \theta_j L^j \qquad (8)$$

where L is the lag operator, μ is the mean and ε_t is white noise with variance σ^2. The model is stationary and invertible when all inverse roots of $\phi(z)$ and $\theta(z)$ lie inside the unit circle. If the two polynomials share a common factor, the factor cancels and the model reduces to a lower order; the parameters of such an over-specified model are poorly determined (Shumway & Stoffer, 2025). The special case ARMA(0,0),

$$y_t = \mu + \varepsilon_t \qquad (9)$$

Describes white noise around a constant mean, for which the best forecast of every future value is μ. A pair of complex inverse AR roots $re^{\pm i\omega}$ implies a damped cycle of period $2\pi/\omega$.

Because the patterns of the sample autocorrelation functions can be ambiguous, all ARMA(p, q) models with p, q = 0, 1, …, 4 (25 models) were estimated. Parameters were estimated by conditional least squares, with residuals computed recursively,

$$\hat{\varepsilon}_t = (y_t - \mu) - \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu) - \sum_{j=1}^{q} \theta_j \hat{\varepsilon}_{t-j} \qquad (10)$$

With pre-sample values set to zero. The residual sum of squares S was minimised with the Levenberg–Marquardt algorithm from multiple starting values, accepting only stationary and invertible solutions. Under normal errors the concentrated log-likelihood is

$$\ell = -\frac{n}{2}\left[1 + \ln(2\pi) + \ln\left(\frac{S}{n}\right)\right] \qquad (11)$$

Models were compared with the Akaike (AIC), Schwarz (SIC) and Hannan–Quinn (HQC) criteria in per-observation form,

$$AIC = \frac{-2\ell + 2k}{n}, \qquad SIC = \frac{-2\ell + k\ln n}{n}, \qquad HQC = \frac{-2\ell + 2k\ln(\ln n)}{n} \qquad (12)$$

Where k is the number of estimated parameters. To make the criteria comparable, all 25 models were estimated on a common sample beginning at observation 5 (n = 224). Nested models were compared with the likelihood-ratio statistic.

$$LR = 2(\ell_1 - \ell_0) \sim \chi^2_{k_1 - k_0} \qquad (13)$$

The coefficient of determination, adjusted R^2, overall F-statistic and Durbin–Watson statistic were also reported. Model adequacy was checked with the residual autocorrelation functions, the Ljung–Box test (5) with $h - (p + q)$ degrees of freedom, the Jarque–Bera test (2) and the inverse roots of the AR and MA polynomials.

2.5 Forecast evaluation

The series was split into a training period (January 2007–December 2024, T = 216) and a hold-out period (January–December 2025, h = 12). Each candidate model was estimated on the training period and used to forecast the hold-out period. Forecasts were compared with observations using

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}(Y_t - \hat{Y}_t)^2}, \qquad MAE = \frac{1}{h}\sum_{t=T+1}^{T+h}\left|Y_t - \hat{Y}_t\right|, \qquad MAPE = \frac{100}{h}\sum_{t=T+1}^{T+h}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \qquad (14)$$

Where Y_t and $\hat{Y}_t$ are the observed and forecast case counts (Hyndman & Athanasopoulos, 2021). A seasonal naïve forecast, $\hat{Y}_t = Y_{t-12}$, served as a benchmark. Forecast bias was tested with a paired-sample t-test on the differences $d_i = Y_i - \hat{Y}_i$,

$$t = \frac{\bar{d}}{s_d/\sqrt{n}} \sim t_{n-1} \qquad (15)$$

of H_0: $\mu_O - \mu_F = 0$ against a two-sided alternative. As an additional check, the selected model was fitted to the data available to the earlier analysis (January 2007–June 2023) and its forecasts were compared with the 30 months observed subsequently.

2.6 Forecasting

The selected model was re-estimated on the full series and used to forecast January 2026 (t = 229) to December 2027 (t = 252). The standard error of the ℓ-step-ahead forecast $\hat{y}_T(\ell)$ is

$$se[\hat{y}_T(\ell)] = \hat{\sigma}\left(\sum_{j=0}^{\ell-1}\psi_j^2\right)^{1/2} \qquad (16)$$

where $\psi_0 = 1$ and ψ_j are the weights of the moving-average representation of (8). The 95% prediction interval for the number of cases is

$$[\exp\{\hat{y}_T(\ell) - 1.96\,se\},\ \exp\{\hat{y}_T(\ell) + 1.96\,se\}] \qquad (17)$$

For ARMA(0,0), $\hat{y}_T(\ell) = \hat{\mu}$ and $se = \hat{\sigma}$ at every horizon. All computations were carried out in Python 3 (NumPy and SciPy), with the Ng–Perron statistics, Ljung–Box test and ARMA estimation programmed directly from the formulas above; the code is available from the corresponding author. All tests used a 5% significance level.

3. RESULTS

3.1 Descriptive statistics

Plateau State recorded an average of 1,055.5 confirmed typhoid cases per month (median 1,051.5; range 916–1,203), with a standard deviation of 71.4 cases and a coefficient of variation of 6.8%

(Table 1). Annual totals were stable, ranging from 12,101 (2008 and 2012) to 13,339 (2013), an average of about 12,670 cases per year; the three most recent years (12,224 in 2023, 12,852 in 2024 and 12,648 in 2025) lay within this range. Both the raw and the log series were approximately symmetric and slightly platykurtic, and the Jarque–Bera test did not reject normality for either (p = 0.093 and 0.091).

Table 1. Descriptive statistics of monthly confirmed typhoid cases, Plateau State, January 2007–December 2025. (n = 228)

Statistic	Confirmed cases	ln(confirmed cases)
Mean	1,055.52	6.9595
Median	1,051.50	6.9580
Minimum	916	6.8200
Maximum	1,203	7.0926
Standard deviation	71.43	0.0679
Coefficient of variation (%)	6.77	—
Skewness	0.048	−0.084
Kurtosis	2.299	2.311
Jarque–Bera statistic (p-value)	4.757 (0.093)	4.784 (0.091)
Total cases	240,659	—

3.2 Trend, variability and seasonality

Figure 1 shows that monthly cases fluctuated irregularly around a constant level throughout the nineteen years. The slope of a regression of the log series on time was not significant (p = 0.746). Month-to-month variability, however, was markedly lower between 2019 and 2022: the standard deviation was 80.5 cases in 2007–2018, 36.1 cases in 2019–2022 and 69.1 cases in 2023–2025. These differences were highly significant (Levene's F = 17.06, p < 0.001), and the rise after 2022 was itself significant (2019–2022 against 2023–2025: F = 11.67, p = 0.001). The period means did not differ (1,055.6, 1,061.0 and 1,047.9 cases; ANOVA F = 0.34, p = 0.709).

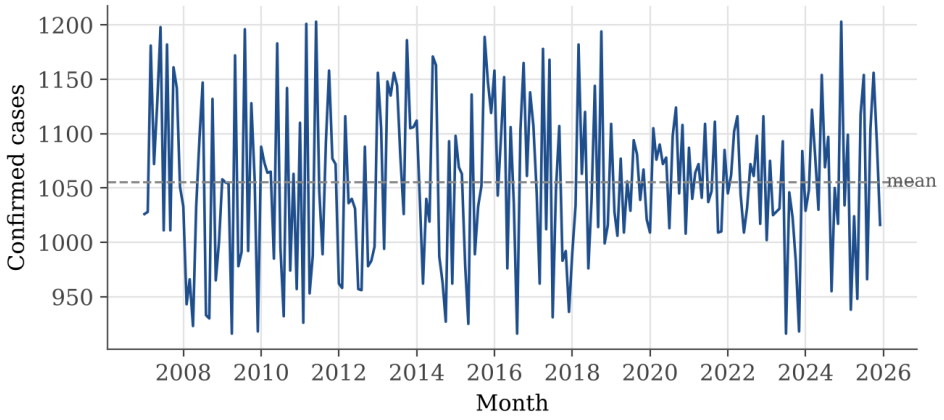


Figure 1. Monthly confirmed typhoid fever cases in Plateau State, Nigeria, January 2007–December 2025.

Mean cases by calendar month ranged only from 1,036.8 (July) to 1,106.3 (June). Neither one-way analysis of variance ($F = 1.57$, $p = 0.110$) nor the Kruskal–Wallis test ($H = 15.99$, df = 11, $p = 0.141$) found a significant difference between calendar months, so no seasonal component was required.

3.3 Autocorrelation and stationarity

All sample autocorrelations and partial autocorrelations of the log series up to lag 24 lay within the 95% limits of ±0.130 (Figure 2). The largest in absolute value were the partial autocorrelations at lags 21 (−0.122) and 10 (−0.116), and the autocorrelation at lag 12 was only −0.033. The Ljung–Box test did not reject the null hypothesis of no autocorrelation at any lag from 1 to 24 ($Q(1) = 1.68$, $p = 0.195$; $Q(12) = 10.96$, $p = 0.532$; $Q(24) = 22.03$, $p = 0.577$; all $p \geq 0.195$).

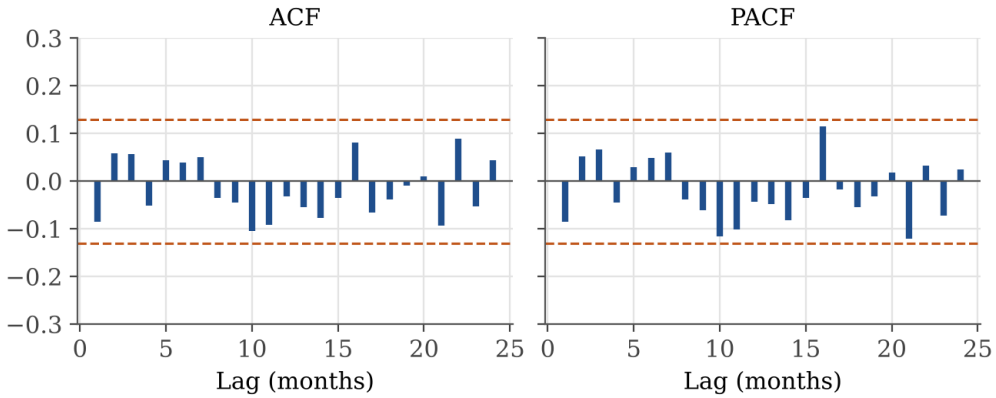


Figure 2. Sample autocorrelation (ACF) and partial autocorrelation (PACF) functions of the log-transformed typhoid series. Dashed lines are the 95% limits, ±1.96/√228 = ±0.130.

All four Ng–Perron statistics rejected the unit-root hypothesis at the 1% level, with and without a linear trend (Table 2), and the ADF test agreed ($\tau = -16.33$ with an intercept and −16.30 with an intercept and trend; 1% critical values about −3.46 and −4.00). The log series is therefore stationary at level, I(0), and can be modelled without differencing.

Table 2. Ng–Perron modified unit root test results for the log typhoid series.

Specification		MZ_α	MZ_t	MSB	MP_T
Intercept	Test statistic	−114.469	−7.565	0.066	0.215
	1% critical value	−13.800	−2.580	0.174	1.780
	5% critical value	−8.100	−1.980	0.233	3.170
Intercept and trend	Test statistic	−114.083	−7.547	0.066	0.818
	1% critical value	−23.800	−3.420	0.143	4.030
	5% critical value	−17.300	−2.910	0.168	5.480

Note: Critical values are the asymptotic values of the Ng–Perron test. The spectral lag length (0) was selected by the Schwarz criterion.

3.4 Model identification and selection

The sample autocorrelation functions showed the pattern of white noise rather than the gradual decay of a mixed ARMA process. Of the 25 candidate models, all three information criteria selected ARMA(0,0) (Table 3). The previously reported ARMA(2,2) model ranked 6th by AIC, 11th by SIC and 10th by HQC. The likelihood-ratio test of ARMA(2,2) against ARMA(0,0) gave

$$LR = 2(288.0744 - 284.9107) = 6.33 \sim \chi^2_4, \qquad p = 0.176 \qquad (18)$$

so the four additional AR and MA parameters did not improve the fit significantly. No other model improved significantly on ARMA(0,0); the largest model, ARMA(4,4), gave LR = 13.26 on 8 degrees of freedom ($p = 0.103$).

Table 3. Information criteria for the 25 candidate ARMA(p, q) models (common sample, $n = 224$)

Model	k	Log-likelihood	AIC	SIC	HQC
ARMA(0,0)[a]	1	284.911	**−2.5349**	**−2.5197**	**−2.5288**
ARMA(0,1)	2	285.654	−2.5326	−2.5022	−2.5203
ARMA(0,2)	3	286.291	−2.5294	−2.4837	−2.5109
ARMA(0,3)	4	286.479	−2.5221	−2.4612	−2.4975
ARMA(0,4)	5	286.876	−2.5168	−2.4406	−2.4860
ARMA(1,0)	2	285.749	−2.5335	−2.5030	−2.5212
ARMA(1,1)	3	285.871	−2.5256	−2.4799	−2.5072
ARMA(1,2)	4	286.388	−2.5213	−2.4604	−2.4967
ARMA(1,3)	5	286.876	−2.5168	−2.4406	−2.4860
ARMA(1,4)	6	286.974	−2.5087	−2.4173	−2.4718
ARMA(2,0)	3	286.095	−2.5276	−2.4819	−2.5092
ARMA(2,1)	4	286.364	−2.5211	−2.4602	−2.4965
ARMA(2,2)[b]	5	288.074	−2.5275	−2.4513	−2.4967
ARMA(2,3)	6	288.366	−2.5211	−2.4297	−2.4842
ARMA(2,4)	7	288.779	−2.5159	−2.4093	−2.4728
ARMA(3,0)	4	286.630	−2.5235	−2.4626	−2.4989
ARMA(3,1)	5	286.893	−2.5169	−2.4407	−2.4862
ARMA(3,2)	6	288.390	−2.5213	−2.4300	−2.4845
ARMA(3,3)	7	288.429	−2.5128	−2.4061	−2.4697
ARMA(3,4)	8	289.291	−2.5115	−2.3897	−2.4623
ARMA(4,0)	5	286.855	−2.5166	−2.4404	−2.4858
ARMA(4,1)	6	286.893	−2.5080	−2.4166	−2.4711
ARMA(4,2)	7	287.436	−2.5039	−2.3973	−2.4609
ARMA(4,3)	8	289.190	−2.5106	−2.3888	−2.4614
ARMA(4,4)	9	291.541	−2.5227	−2.3856	−2.4674

Note: [a] Model selected by all three criteria (minimum values in bold). [b] Model selected by Amua (2024). k = number of estimated parameters.

3.5 Parameter estimates and model comparison

The selected model, estimated on the full series, is

$$\ln Y_t = 6.9595 + \varepsilon_t, \qquad \varepsilon_t \sim WN(0,\ 0.06785^2) \qquad (19)$$

with a standard error of 0.0045 for the constant (t = 1548.7, $p < 0.001$). The constant corresponds to $e^{6.9595} \approx 1{,}053$ cases, the geometric mean of the monthly counts. The fitted ARMA(2,2) comparison model is

$$\ln Y_t = 6.9598 - 0.5955(\ln Y_{t-1} - 6.9598) - 0.9530(\ln Y_{t-2} - 6.9598) + \varepsilon_t + 0.5668\varepsilon_{t-1} + 0.9841\varepsilon_{t-2} \qquad (20)$$

Each ARMA(2,2) coefficient was individually significant (Table 4), yet the model explained only 2.7% of the variation in the log series (adjusted R^2 = 0.0096), and its overall F-statistic was not significant (F = 1.55, p = 0.190). The explanation lies in the inverse roots: the AR roots (−0.298 ± 0.930i, modulus 0.976) and MA roots (−0.283 ± 0.951i, modulus 0.992) almost coincide, so the AR and MA factors nearly cancel and the model collapses towards ARMA(0,0). The MA modulus of 0.992 also places the model at the edge of non-invertibility. The angle of the complex AR roots (107.8°) implies a cycle of about 3.3 months, which the MA factor cancels and which is not visible in the data (Figure 2).

Table 4. Parameter estimates and goodness of fit of the selected and comparison models. (full sample)

	ARMA(0,0)	**ARMA(1,0)**	**ARMA(2,2)**
Constant, μ (SE)	6.9595 (0.0045)	—	6.9598 (0.0045)
ϕ_1 (SE)	—	—	−0.5955 (0.0323)
ϕ_2 (SE)	—	—	−0.9530 (0.0321)
θ_1 (SE)	—	—	0.5668 (0.0198)
θ_2 (SE)	—	—	0.9841 (0.0194)
Observations used	228	227	226
Residual standard error	0.06785	0.06788	0.06778
Log-likelihood	290.396	289.527	290.110
AIC	−2.5386	−2.5333	−2.5231
SIC	−2.5235	−2.5031	−2.4474
HQC	−2.5325	−2.5211	−2.4926
R^2 (adjusted R^2)	0.000 (0.000)	0.007 (0.003)	0.027 (0.010)
Durbin–Watson	2.169	1.991	2.078
Ljung–Box $Q(24)$ (p-value)	22.03 (0.577)	—	17.42 (0.625)

Note: SE = standard error. All ARMA(2,2) coefficients have $p < 0.0001$. Ljung–Box degrees of freedom are $24 - (p + q)$. ARMA(1,0) coefficient estimates are omitted for brevity.

Both ARMA(0,0) and ARMA(2,2) passed the diagnostic checks: their residual autocorrelations all lay within the 95% limits, and the Ljung–Box test was non-significant at every lag (all $p > 0.20$ for ARMA(2,2)). Normality of the ARMA(0,0) residuals was not rejected (JB = 4.78, $p = 0.091$). Since ARMA(0,0) achieves an adequate fit with one parameter rather than five, the principle of parsimony favours it.

3.6 Forecast evaluation

On the 2025 hold-out year, the three ARMA models forecast almost equally well (MAPE 6.27–6.38%; RMSE 72.8–73.9 cases), and all were clearly better than the seasonal naïve benchmark (MAPE 9.22%) (Table 5). The differences among the ARMA models amounted to about one case per month: the ARMA(2,2) forecast oscillated within about ten cases of the constant ARMA(0,0) forecast, while observed counts moved by 100 cases or more (Figure 3). Monthly errors of the ARMA(0,0) forecast ranged from −115 cases (March 2025) to +103 cases (October 2025). Out-of-sample errors were somewhat larger than in-sample errors (MAPE 6.37% against 5.54%), reflecting the greater variability of 2025 (standard deviation 77 cases, against 71 cases in 2007–2024).

Table 5. Forecast accuracy and bias of competing models (training: January 2007–December 2024; hold-out: January–December 2025.)

Model	In-sample RMSE	In-sample MAPE (%)	Hold-out RMSE	Hold-out MAE	Hold-out MAPE (%)	Paired *t* (*p*)
ARMA(0,0)	71.17	5.54	73.93	66.33	6.37	0.036 (0.972)
ARMA(1,0)	71.03	5.52	73.69	65.28	6.27	—
ARMA(2,2)	70.38	5.47	72.82	66.41	6.38	0.038 (0.970)
Seasonal naïve	—	—	110.18	95.33	9.22	—

Note: Paired *t*-tests have 11 degrees of freedom. For ARMA(0,0), the mean difference (observed − forecast) was 0.79 cases (95% CI −48.26 to 49.85).

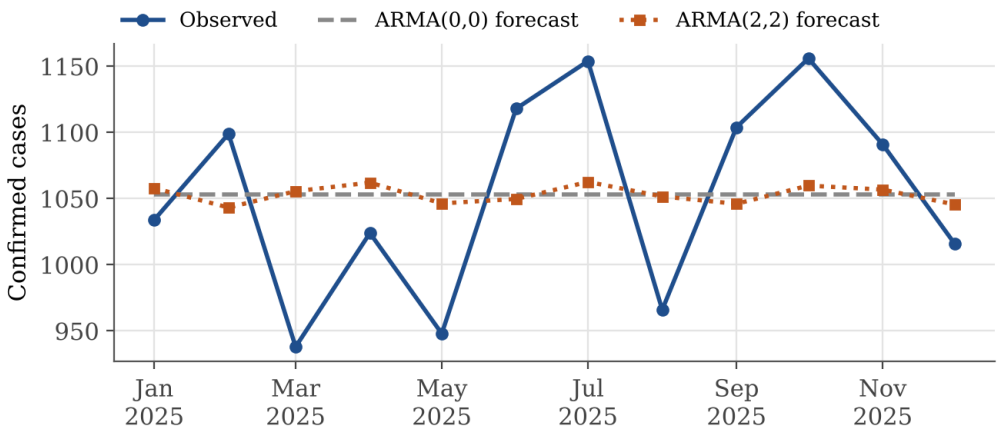


Figure 3. Observed and forecast typhoid cases in the hold-out period, January–December 2025.

The paired-sample *t*-test found no significant difference between observed and forecast values for ARMA(0,0) ($t = 0.036$, df = 11, $p = 0.972$), and the 95% confidence interval of the mean difference contained zero; the result was the same for ARMA(2,2) ($t = 0.038$, $p = 0.970$). The forecasts were therefore unbiased over the hold-out year.

The longer check gave a consistent result. ARMA(0,0) fitted to January 2007–June 2023 forecast 1,054 cases per month, with a 95% prediction interval of 924 to 1,203. Of the 30 months subsequently observed (July 2023–December 2025), 28 (93%) lay within this interval, close to the nominal 95%; the two exceptions, July 2023 (916 cases) and November 2023 (918 cases), lay just below the lower limit. Over these 30 months the forecast had a MAPE of 5.82%, and the mean observed count (1,049 cases) did not differ significantly from the forecast (one-sample $t = -0.38$, $p = 0.709$).

3.7 Forecasts for 2026–2027

Re-estimated on the full series, ARMA(0,0) forecasts a median of about 1,053 confirmed cases per month from January 2026 to December 2027, with a 95% prediction interval of 922 to 1,203 cases ($e^{6.9595 \pm 1.96 \times 0.0679}$) (Figure 4). The forecast mean, $e^{\hat{\mu}+\hat{\sigma}^2/2}$, is 1,056 cases. Over the 24 months this amounts to about 25,270 cases, or roughly 12,640 per year. The ARMA(2,2) point forecasts differed from these by no more than three cases in any month. The forecasts show no decreasing trend.

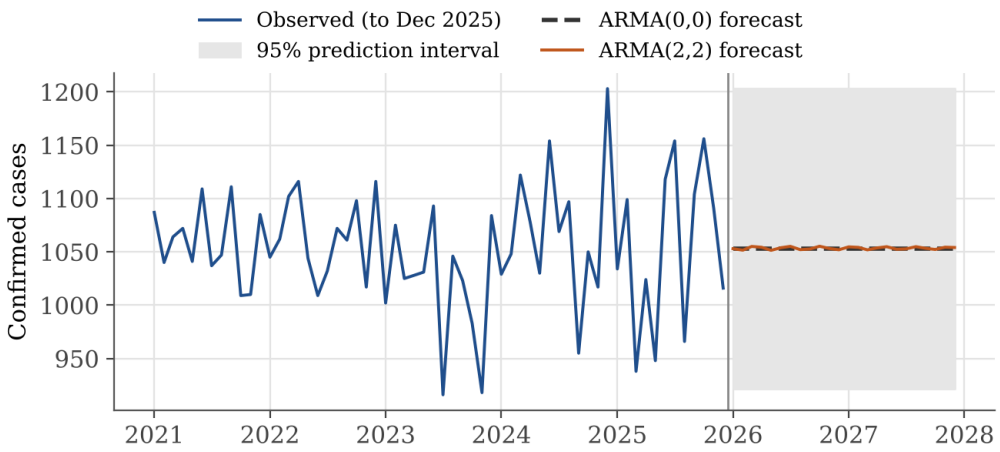


Figure 4. Observed series (2021–2025) and forecasts of monthly typhoid fever cases in Plateau State to December 2027, with the 95% prediction interval of the ARMA(0,0) model.

4. DISCUSSION

This study found that monthly confirmed typhoid cases in Plateau State from 2007 to 2025 behave as a stationary, non-seasonal and serially uncorrelated series around a constant level of about 1,053 cases. Accordingly, all three information criteria selected the white-noise model ARMA(0,0), which forecast both a hold-out year and the 30 months after the earlier analysis's data accurately and without bias, and outperformed a seasonal naïve benchmark by about three percentage points of MAPE.

The results differ from those of the earlier analysis of the same series (Amua, 2024) in three respects. First, the ARMA(2,2) model selected there is over-parameterised: its AR and MA roots nearly coincide, so the extra terms cancel one another, and it improves neither the likelihood significantly nor the forecasts. Individually significant coefficients combined with negligible joint explanatory power are a known symptom of such near-common factors (Shumway & Stoffer, 2025), and they illustrate why information criteria and benchmark comparisons should be used together with coefficient tests. The reported R^2 of 75.75% could not be reproduced from the published data or the extended series; the model explains 2.7% of the variation. Second, the eight-month "life cycle" implied there is not supported: the angle of the complex AR roots implies a cycle of about 3.3 months, which is in any case cancelled by the MA factor, and the periodicity of a statistical model of case counts carries no information about the clinical course of what is an acute illness (Meiring et al., 2023). Third, the forecasts do not show a decline. Including ARMA(0,0) in the candidate set and validating forecasts on withheld data, as recommended in forecasting practice (Hyndman & Athanasopoulos, 2021),

would have revealed these issues; the present findings therefore have a methodological lesson beyond Plateau State.

The absence of seasonality contrasts with recurring seasonal peaks in reported typhoid in Ghana's Eastern Region (Baffoe et al., 2026) and with a wet-season peak in *S.* Typhi detected by environmental surveillance in Ibadan (Kehinde et al., 2025). One plausible explanation is that serologically confirmed counts include many false-positive Widal results (Tegene & Eshetie, 2025), which would blur any seasonal signal in true infections. Similarly, the advantage of flexible methods such as Holt–Winters or hybrid ARIMA–LSTM models reported for foodborne diseases in China (Xian et al., 2023; Du et al., 2025) depends on seasonality or autocorrelation that this series does not have. As in Aliade, Benue State, where an ARIMA model outperformed naïve benchmarks (Jighjigh et al., 2025), the ARMA models here outperformed the seasonal naïve forecast, but here the simplest ARMA model was sufficient.

The stable level of about 12,600 to 12,700 cases a year is consistent with the high and persistent typhoid burden measured in Nigeria and other African countries (Marks et al., 2024) and contrasts with the global decline in age-standardised incidence since 1990 (Shi & You, 2025). For practice, the findings have three implications. First, prevention should be sustained rather than scaled back in expectation of a decline: continued investment in safe water, sanitation and food hygiene addresses the main routes of transmission (Kim et al., 2023; Okyere et al., 2025), and introduction of typhoid conjugate vaccine, recommended by WHO for endemic settings and eligible for Gavi support, should be pursued (WHO, 2023; Ashikeni et al., 2026). Second, the upper 95% prediction limit of about 1,203 cases, or a run of monthly counts above about 1,150, provides a simple, validated alert threshold for investigating possible outbreaks. Third, expanding blood-culture confirmation at sentinel facilities would make reported counts a better measure of true typhoid incidence.

The significantly reduced month-to-month variability in 2019–2022, with an unchanged mean and a return to earlier variability from 2023, is a new observation. Because a genuine change in transmission would be expected to affect the level as well as the spread of cases, the pattern more probably reflects a change in reporting, aggregation or laboratory practice during that period. We recommend that it be verified with the data custodians, and it is a reminder that routine surveillance series should be checked for changes in data-generating processes before they are modelled.

The study has limitations. The counts are largely based on serological (Widal) confirmation and may include false-positive cases. The data are aggregated for the whole state, so

differences between local government areas, age groups and sexes could not be examined. The analysis was restricted to univariate ARMA models; climatic, environmental and socio-economic covariates were not modelled. The hold-out evaluation covered a single year, although the 30-month check on the earlier forecast supports its conclusions. Its strengths are the long 19-year series, the exhaustive comparison of 25 models on a common sample, the inclusion of a white-noise benchmark and a likelihood-ratio test, and two independent out-of-sample validations.

Supplementary Material

Table S1. Monthly confirmed typhoid fever cases in Plateau State, Nigeria, January 2007–December 2025.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2007	1026	1028	1181	1072	1128	1198	1011	1182	1011	1161	1142	1051	13191
2008	1033	943	966	923	1033	1096	1147	933	930	1132	965	1000	12101
2009	1058	1055	1054	916	1172	978	991	1196	992	1128	1058	918	12516
2010	1088	1073	1064	1065	985	1183	995	932	1142	974	1063	957	12521
2011	1110	926	1201	953	988	1203	1047	989	1092	1158	1077	1072	12816
2012	962	958	1116	1036	1040	1031	957	956	1088	978	983	996	12101
2013	1156	1105	994	1148	1135	1156	1144	1078	1026	1186	1105	1106	13339
2014	1112	1035	962	1040	1019	1171	1163	987	963	927	1093	962	12434
2015	1098	1069	1063	979	925	1136	989	1033	1052	1189	1147	1119	12799
2016	1158	1043	1094	1152	976	1106	1036	916	1103	1165	1061	1138	12948
2017	1107	1045	962	1178	1012	1168	931	1049	1107	983	992	936	12470
2018	990	1034	1182	1063	1120	976	1039	1144	1014	1194	999	1016	12771
2019	1109	1028	1006	1077	1009	1056	1029	1094	1081	1039	1067	1021	12616
2020	1009	1105	1076	1090	1072	1078	1013	1098	1124	1045	1108	1008	12826
2021	1087	1040	1064	1072	1041	1109	1037	1047	1111	1009	1010	1085	12712
2022	1045	1062	1102	1116	1044	1009	1032	1072	1061	1098	1017	1116	12774
2023	1002	1075	1025	1028	1031	1093	916	1046	1023	983	918	1084	12224
2024	1029	1048	1122	1078	1030	1154	1069	1097	955	1050	1017	1203	12852
2025	1034	1099	938	1024	948	1118	1154	966	1104	1156	1091	1016	12648

Source: Epidemiology Unit, Plateau State Ministry of Health, Jos.

5. CONCLUSION

Monthly typhoid fever morbidity in Plateau State, Nigeria, behaves as stationary white noise around a constant and high level of about 1,053 confirmed cases per month. The parsimonious ARMA(0,0) model forecasts it as accurately as more complex ARMA models and better than a seasonal naïve benchmark, and the more complex ARMA(2,2) model previously proposed is over-parameterised. There is no evidence that typhoid in the state is declining: about 12,640 cases a year are expected in 2026 and 2027. The forecasts and their

prediction interval provide a validated planning baseline and alert threshold. Future work should test these forecasts against 2026–2027 data as they become available, investigate the 2019–2022 change in variability with structural-break or conditional heteroscedasticity models, incorporate rainfall, temperature and water and sanitation coverage as covariates, and disaggregate the analysis by local government area, age and sex.

Declarations

Data availability: The monthly case counts analysed in this study are provided in Supplementary Table S1. The analysis code is available from the corresponding author on reasonable request.

Ethical considerations: The study used aggregated, anonymised secondary surveillance data obtained from the Epidemiology Unit of the Plateau State Ministry of Health, Jos. [State the permission or ethical approval obtained, with reference number, or the exemption that applies.]

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Conflict of interest: The authors declare no conflict of interest.

Author contributions: [Adjust as appropriate.] Y. F. Obalisa: conceptualisation, data curation, formal analysis, writing – original draft. K. E. Lasisi: supervision, methodology, writing – review and editing. E. O. Ben: supervision, validation, writing – review and editing. B. A. Garba: methodology, software, formal analysis, writing – review and editing. All authors read and approved the final manuscript.

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