**Faculty of Natural and Applied Sciences Journal of Health, Sports Science and Recreation**
**Print ISSN: 3026-9644 e-ISSN: 3043-6346**
www.fnasjournals.com
**Volume 2; Issue 4; December 2025; Page No. 1-14.**
**DOI:** https://doi.org/10.63561/jhssr.v2i4.1105

# Epidemiological Trends and Dynamics of Typhoid Fever in North-Central Nigeria

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**Abstract**
This study investigates the epidemiological trends and dynamics of typhoid fever in North-Central Nigeria by analyzing cases recorded at Grimard Catholic Hospital, Anyigba, from 2015 to 2024. Monthly time series data of positive and negative typhoid tests were examined using descriptive and inferential statistics to identify patterns, trends, and seasonal variations. Positive cases consistently outnumbered negative ones, indicating a sustained disease burden. Time series decomposition revealed clear seasonal structures and a slight downward trend, suggesting gradual improvements in public health conditions. Stationarity tests confirmed the data's suitability for modeling. Forecasting methods, including ARIMA, exponential smoothing, and Fourier series, captured the underlying trends effectively, with ARIMA providing the strongest predictive performance. Seasonal peaks during rainy months underscored the influence of environmental factors on transmission dynamics. These findings offer critical insights into typhoid fever patterns in North-Central Nigeria and provide a statistical basis for designing targeted interventions and strengthening regional public health planning.

**Keywords:** Typhoid fever, epidemiology, time series, Nigeria, Grimard Hospital, trend analysis

## Introduction

In low- and middle-income countries (LMICs), where poor sanitation, contaminated drinking water, and limited access to healthcare support ongoing transmission, typhoid fever remains a serious public health concern. Every year, it affects 11 to 20 million people worldwide and results in approximately 128,000 deaths; South Asia and sub-Saharan Africa bear the brunt of this burden. With a high incidence in urban and semi-urban areas where overburdened public health services and deficiencies in environmental cleanliness continue, Nigeria continues to be particularly afflicted. Due to the rise of non-typhoidal Salmonella strains and Salmonella Paratyphi, as well as growing antibiotic resistance, the worldwide epidemiology of typhoid has changed. Azithromycin is still useful for simple cases, but resistance to fluoroquinolones and third-generation cephalosporins is growing (Crump & Mintz, 2010). Timely outbreaks are hampered by inadequate surveillance infrastructure and limited genetic monitoring.detection and response in most endemic settings (Han et al., 2023; Meiring et al., 2023).

Typhoid transmission in Nigeria is exacerbated by seasonal and infrastructure factors. Outbreaks are encouraged by urbanisation without corresponding improvements in sanitation, especially during rainy seasons when flooding and water contamination take place. Research by Omoregie and Okoro (2024), Akawu et al. (2018), and Ibor et al. (2016) shows that rainfall has a significant impact on the incidence of disease, frequently with patterns that are particular to age and gender. Despite these discoveries, the majority of Nigerian research is cross-sectional and lacks the longitudinal viewpoints necessary to comprehend long-term temporal dynamics and the interaction of public health, infrastructure, and environmental solutions (Obimakinde & Simon-Oke, 2017; Gyuse et al., 2018).

Prince Abubakar Audu University is located in Anyigba, a semi-urban district in Kogi State that is a crucial, understudied high-risk area with poor waste disposal, limited access to drinkable water, dense population, and inadequate sanitation. The town's main referral facility, Grimard Catholic Hospital, keeps thorough clinical records that offer a special chance for thorough epidemiological study.

In order to improve disease monitoring in North-Central Nigeria and guide evidence-based treatments, this study examined the epidemiological trends, seasonal dynamics, and temporal patterns of typhoid fever at Grimard Catholic Hospital during a ten-year period (2015–2024). In particular, it looked at incidence trends over time, found seasonal peaks during rainy months, assessed the impact of public health, infrastructure, and environmental interventions on observed fluctuations, and evaluated the predictive performance of time series models (ARIMA, exponential smoothing, and Fourier series) for short-term forecasting. This study offers new, data-driven insights into disease dynamics by combining longitudinal hospital-based data with sophisticated time series modelling. This allows for precise targeting of public health strategies, optimises resource allocation, and advances our knowledge of typhoid epidemiology in high-burden Nigerian communities.

The remainder of this work is organised as follows: The study region, data gathering methods, and the analytical and forecasting techniques used are all covered in Section 2's Materials and Methods section. The results, which include trend analysis, forecasting of typhoid fever cases, time series visualisation and decomposition, and descriptive statistics, are presented in Section 3. The results are discussed in Section 4 in relation to seasonal dynamics, public health initiatives, and regional epidemiology. The study is finally concluded in Section 5, which highlights important findings, constraints, and suggestions for disease prevention and surveillance in North-Central Nigeria.

## Materials and Methods

### Study Area

This study was conducted in Anyigba, a semi-urban town situated in Dekina Local Government Area of Kogi State, North-Central Nigeria. It lies between latitudes 7°15’N–7°29’N and longitudes 7°11’E–7°32’E, at an elevation of approximately 385 meters above sea level, and spans a land area of 420 square kilometers. The town’s estimated population is 189,976 residents (Ifatimehin et al., 2009). Prince Abubakar Audu University and other small and medium-sized businesses are located in Anyigba, which is an important commercial and educational hub. Nevertheless, the town still has issues including poor waste management, inadequate water sanitation, and inadequate healthcare infrastructure, which contribute to the high prevalence of waterborne illnesses like typhoid fever, despite the institutional presence and population development. Located in the heart of Anyigba, Grimard Catholic Hospital is a significant medical facility that provides general and referral services to the local rural and urban populations. With inpatient facilities, diagnostic labs, and skilled medical staff, it is well-equipped to handle infectious infections. It is a perfect source for doing a retrospective analysis of typhoid fever trends because of its excellent record-keeping and community importance.

#### Data Collection

This study used a retrospective review of Grimard Catholic Hospital patient records covering a 10-year period from January 2015 to December 2024. The review concentrated on patients who had been diagnosed with typhoid fever, either by laboratory confirmation (such as the Widal test or blood culture) or clinical assessment. Age, sex, the date of diagnosis, the kind of diagnosis (clinical or laboratory), and the results of treatment were among the variables that were extracted. The dataset was thoroughly cleaned to eliminate duplicate entries, discrepancies, and incomplete information before analysis. The hospital's ethics review board granted the study ethical permission. All individually identifiable information was eliminated to guarantee confidentiality, preserving patient anonymity throughout the study.

#### Analytical Approach

The study used a variety of statistical and mathematical techniques, such as time series decomposition, regression modelling, seasonal analysis, and forecasting, to investigate the temporal dynamics of typhoid disease in Anyigba. These instruments made it easier to identify cyclical patterns, long-term trends, and statistically significant changes in incidence over time.

#### Time Series Construction

Monthly (or annual) counts of typhoid cases were compiled into a univariate time series denoted as:

$$\{y_1, y_2, ..., y_n\} \tag{1}$$

where $y_t$ represents the number of cases at time $t$, and $n$ is the number of time periods observed.


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### Time Series Decomposition

The observed series was decomposed using an additive model:

$$y_t = T_t + S_t + R_t \tag{2}$$

where $T_t$ represents the trend component capturing the long-term direction of the data, $S_t$ denotes seasonality reflecting periodic fluctuations (such as monthly or seasonal patterns), and $R_t$ accounts for the residual or irregular variations not explained by the trend or seasonal effects.

### Trend Estimation Techniques

To estimate $T_t$, two primary methods were used:
Simple Moving Average (SMA):

$$T_t = \frac{1}{k}\sum_{i=t-\frac{k-1}{2}}^{t+\frac{k-1}{2}} y_i \tag{3}$$

where $k$ is the smoothing window size.
Exponential Smoothing:

$$\hat{y}_t = \alpha y_t + (1-\alpha)\hat{y}_{t-1} \tag{4}$$

Here, $\alpha \in [0, 1]$ is the smoothing constant that controls responsiveness to recent data.

### Regression Modeling for Trend Detection

A linear regression model was fitted to quantify the relationship between time and typhoid case counts:

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{5}$$

In this model, $\beta_0$ is the intercept, $\beta_1$ is the trend coefficient (slope) indicating the direction and magnitude of change over time, and $\varepsilon_t$ represents the random error term capturing unexplained variability.

### Parameter Estimation and Significance Testing

Model parameters were estimated using Ordinary Least Squares (OLS), minimizing the residual sum of squares (RSS):

$$RSS = \sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{6}$$

To test the significance of the trend, a $t$-test was applied to $\beta_1$:

$$t = \frac{\hat{\beta}_1}{SE(\hat{\beta}_1)} \tag{7}$$

A statistically significant trend was inferred if the absolute $t$-value exceeded the critical value at a chosen significance level (typically $\alpha = 0.05$).


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Seasonal Analysis Using Fourier Series

To capture monthly seasonal variations, the seasonal component $S_t$ was modeled using Fourier series:

$$S_t = \sum_{k=1}^{K} \left( a_k \cos\left(\frac{2\pi kt}{12}\right) + b_k \sin\left(\frac{2\pi kt}{12}\right) \right) \tag{8}$$

where $a_k$ and $b_k$ are the Fourier coefficients, and $K$ is the number of harmonics included. Alternatively, classical decomposition and STL (Seasonal and Trend decomposition using Loess) were employed to isolate the seasonal component directly from the observed series.

Forecasting Models

Once trends and seasonal patterns were established, future values were forecast using:

Linear Trend Projection:

$$\hat{y}_{t+h} = \hat{\beta}_0 + \hat{\beta}_1 (t+h) \tag{9}$$

Exponential Smoothing Forecast:

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha)\hat{y}_t \tag{10}$$

where $h$ is the forecast horizon.

Model Evaluation Metrics

To assess the performance and reliability of the forecasting models, the following error metrics were computed:

1. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| y_t - \hat{y}_t \right| \tag{11}$$

2. Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{12}$$

3. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{13}$$

These metrics provided a comprehensive assessment of model accuracy and were critical for validating the robustness of the forecasts used to inform public health interventions.

**Results**

This section provides an in-depth epidemiological analysis of typhoid fever cases recorded at Grimard Catholic Hospital, Anyigba, from 2015 to 2024. The analysis encompasses data presentation, descriptive statistics, time series visualization and decomposition, stationarity testing, model fitting, and forecasting. The findings offer critical insights into temporal patterns, seasonality, and long-term dynamics of typhoid incidence, supporting data-driven decisions for public health interventions.

## Data Overview

Table 1 presents a detailed monthly distribution of typhoid test results, classified as positive and negative, over the 10-year period. This tabulation forms the foundation for detecting patterns and analyzing changes in disease burden over time.

Table 1: Monthly Typhoid Cases (Positive and Negative) at Grimard Catholic Hospital, Anyigba (2015–2024)

| Month | Case | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| January | -ve | 25 | 18 | 20 | 19 | 14 | 19 | 14 | 12 | 10 | 16 | 167 |
| | +ve | 87 | 75 | 78 | 84 | 91 | 69 | 86 | 54 | 42 | 72 | 738 |
| February | -ve | 28 | 24 | 18 | 23 | 25 | 14 | 16 | 18 | 16 | 18 | 206 |
| | +ve | 67 | 70 | 62 | 59 | 71 | 80 | 82 | 67 | 71 | 76 | 705 |
| March | -ve | 21 | 16 | 22 | 24 | 19 | 17 | 18 | 15 | 10 | 16 | 178 |
| | +ve | 71 | 69 | 75 | 62 | 71 | 69 | 67 | 81 | 83 | 79 | 728 |
| April | -ve | 18 | 24 | 19 | 25 | 21 | 23 | 17 | 19 | 21 | 18 | 205 |
| | +ve | 69 | 72 | 65 | 58 | 75 | 43 | 49 | 53 | 70 | 79 | 633 |
| May | -ve | 15 | 21 | 27 | 18 | 19 | 16 | 14 | 23 | 21 | 19 | 193 |
| | +ve | 82 | 79 | 24 | 69 | 73 | 80 | 70 | 59 | 63 | 68 | 667 |
| June | -ve | 23 | 18 | 14 | 19 | 25 | 23 | 16 | 13 | 17 | 15 | 183 |
| | +ve | 71 | 65 | 70 | 65 | 57 | 51 | 75 | 80 | 72 | 61 | 667 |
| July | -ve | 14 | 19 | 25 | 17 | 21 | 19 | 23 | 15 | 10 | 13 | 176 |
| | +ve | 51 | 68 | 71 | 67 | 75 | 56 | 42 | 59 | 78 | 62 | 629 |
| August | -ve | 18 | 23 | 17 | 21 | 25 | 21 | 18 | 17 | 15 | 18 | 193 |
| | +ve | 69 | 78 | 63 | 73 | 53 | 58 | 71 | 72 | 81 | 58 | 676 |
| September | -ve | 21 | 25 | 19 | 14 | 17 | 10 | 18 | 15 | 21 | 13 | 173 |
| | +ve | 67 | 59 | 78 | 68 | 51 | 56 | 63 | 72 | 58 | 65 | 637 |
| October | -ve | 23 | 14 | 18 | 12 | 17 | 15 | 21 | 25 | 14 | 10 | 179 |
| | +ve | 61 | 74 | 62 | 80 | 69 | 57 | 65 | 55 | 49 | 45 | 617 |
| November | -ve | 14 | 21 | 23 | 17 | 19 | 15 | 12 | 19 | 12 | 16 | 188 |
| | +ve | 69 | 76 | 53 | 67 | 77 | 81 | 24 | 75 | 80 | 51 | 653 |
| December | -ve | 17 | 13 | 19 | 14 | 21 | 28 | 23 | 20 | 23 | 17 | 195 |
| | +ve | 62 | 45 | 49 | 78 | 59 | 63 | 59 | 63 | 63 | 49 | 590 |

## Time Series Visualization

The time series plots in Figure 1 depict monthly counts of positive and negative typhoid fever cases from 2015 to 2024. Both series exhibit noticeable seasonal patterns, with periodic peaks suggesting environmental or behavioral influences. A slight downward trend in positive cases is observable, indicating potential improvement in disease control. In contrast, negative cases show more fluctuation, possibly reflecting changes in testing rates or diagnostic practices over time.


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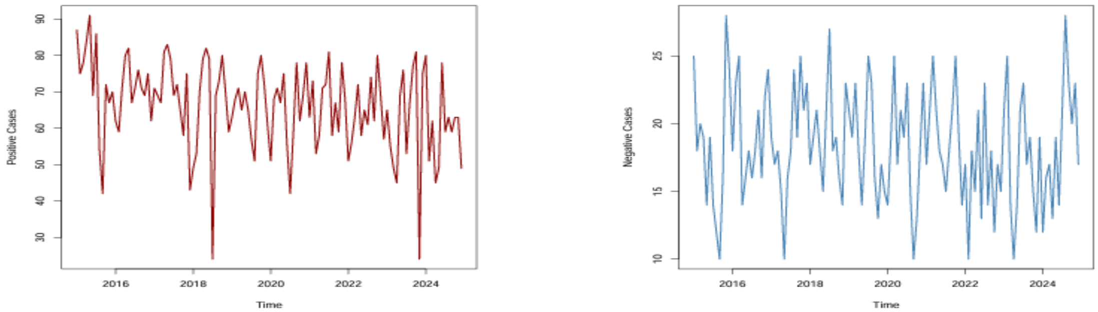


(a): Positive (b): Negative

Figure 1: Monthly Positive and Negative Typhoid Fever Cases (2015–2024)

Figure 1 showed clear month-to-month fluctuations in both positive and negative typhoid cases, with noticeable peaks and troughs across years, indicating recurring seasonal patterns and sustained variability throughout the 2015–2024 period.

## Descriptive Statistical Analysis

Table 2 presents summary statistics of monthly typhoid cases from 2015 to 2024, highlighting measures of central tendency and dispersion. Positive cases consistently outnumber negative cases across all statistical measures, suggesting a significantly higher burden of confirmed infections among tested patients. The median positive count (68.5) is notably higher than that of negative cases (18). Both distributions exhibit moderate variability between their respective minimum and maximum values, further emphasizing the disparity in case burden.

Table 2: Summary Statistics of Monthly Typhoid Cases (2015–2024)

| Statistic | Positive Cases | Negative Cases |
|---|---|---|
| Minimum | 24 | 10 |
| 1st Quartile | 59 | 15 |
| Median | 68.5 | 18 |
| Mean | 66.22 | 18.31 |
| 3rd Quartile | 75 | 21 |
| Maximum | 91 | 28 |

Table 2 showed that positive typhoid cases consistently exceed negative cases, with higher mean and median values, indicating a substantial disease burden, while both series exhibit moderate variability across the 10-year period.

## Time Series Decomposition

To uncover underlying patterns in the data, additive decomposition was applied to the monthly time series of typhoid cases. As shown in Figure 2, the decomposition isolates three primary components for both the positive (Figure 2a) and negative (Figure 2b) case series.

The trend component exhibits a mild downward trajectory, particularly in the positive cases, suggesting a gradual decline in typhoid incidence over the observed period. The seasonal component reveals regular, recurring fluctuations with distinct peaks and troughs, indicating the presence of seasonal influences on disease occurrence. Lastly, the random component captures short-term irregularities and stochastic variations not explained by trend or seasonality, which may reflect unforeseen external factors or data noise.


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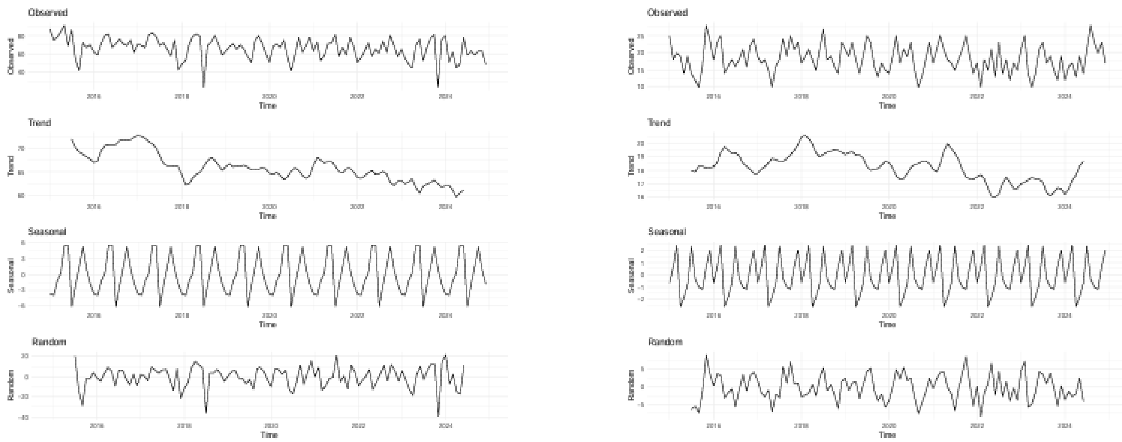


(a): Positive (b): Negative

Figure 2: Decomposition of Positive and Negative Typhoid Fever Cases (Additive Model)

The decomposition in Figure 2 revealed clear seasonal, trend, and irregular components in both positive and negative cases, showing consistent yearly patterns, gradual trend shifts, and short-term fluctuations that together explain the overall dynamics of typhoid incidence.

Stationarity Assessment

Table 3 presents the Augmented Dickey-Fuller test results for both positive and negative ty- typhoid case series. The test statistics are significantly negative, with p-values below 0.05, indicating rejection of the null hypothesis of non-stationarity. Thus, both series are considered stationary, justifying their suitability for time series modeling and forecasting without additional transformation.

Table 3: Augmented Dickey-Fuller Test Results

| Series | Dickey-Fuller Stat | p-value | Conclusion |
|---|---|---|---|
| Positive Cases | -3.9961 | 0.0118 | Stationary |
| Negative Cases | -5.2966 | $< 0.01$ | Stationary |

Table 3 indicated that both positive and negative typhoid case series are stationary, with Dickey-Fuller statistics significantly negative and p-values below 0.05, justifying their suitability for time series modeling and forecasting.

Transformation: Differencing and Deseasonalization

To further refine the data for modeling, differencing and deseasonalisation were applied. Differencing removes trends, enhancing stationarity by eliminating non-constant mean behavior while preserving seasonal and irregular components. Figure 3 illustrates the first-order differenced series for positive (a) and negative (b) typhoid cases. The resulting series are stabilized and centered around zero, indicating successful removal of the trend component. This trans- formation prepares the data for further time series modeling. Deseasonalisation, on the other hand, isolates the non-seasonal behavior of the series, as shown in Figure 4.


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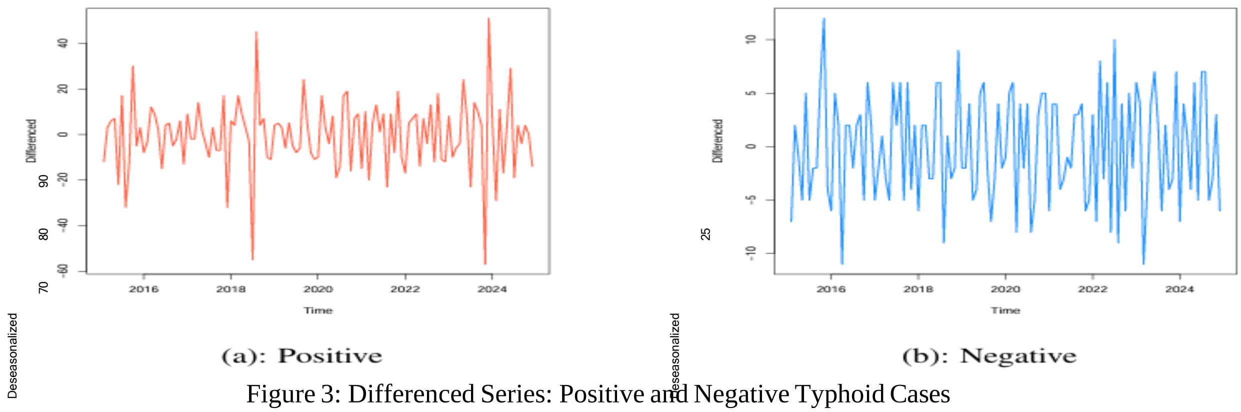
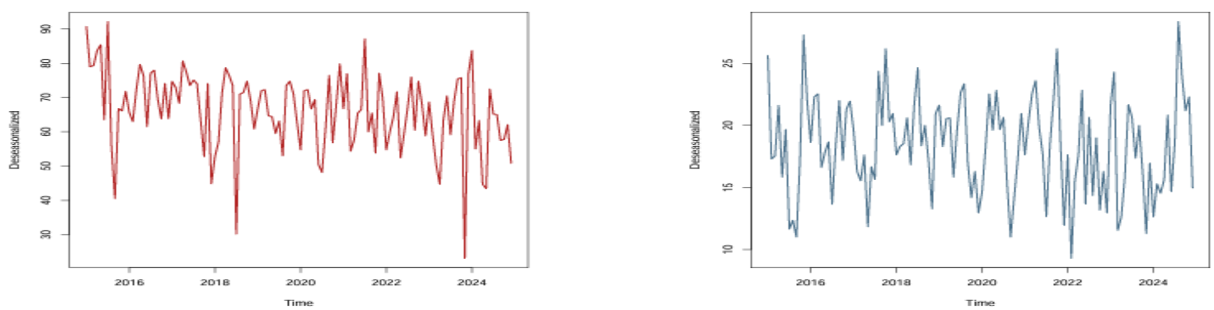



(a): Positive (b): Negative

Figure 3: Differenced Series: Positive and Negative Typhoid Cases



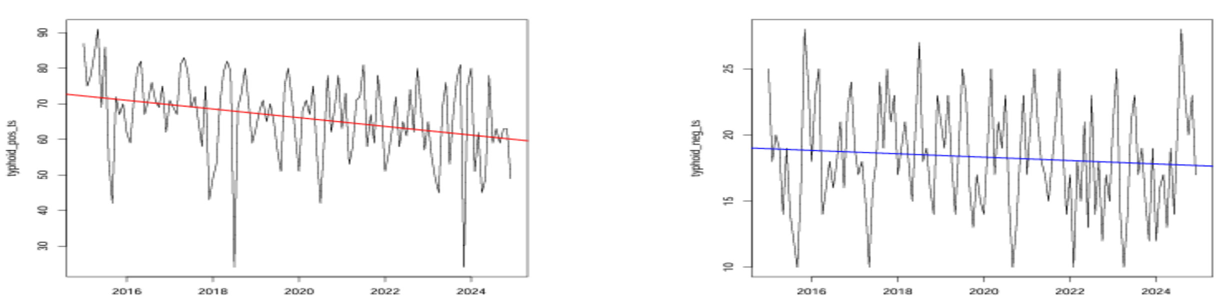

(a): Positive (b): Negative

Figure 4: Deseasonalised Series: Positive and Negative Typhoid Cases

Figures 3 and 4 showed that differencing and deseasonalisation effectively stabilized the typhoid case series, removing trends and seasonal effects. This prepares the data for accurate time series modeling, highlighting underlying stochastic fluctuations.

**Trend Modeling Using Linear Regression**

Linear regression models were fitted to both series to quantify long-term trends. Table 4 shows the estimated coefficients from the linear trend models for positive and negative typhoid cases, while Figure 5 visualizes these trends. Both series exhibit negative slope values, indicating a gradual decline over time. The similar magnitudes of the slopes suggest that the rates of decrease in positive and negative cases are nearly identical, reflecting a mild but consistent downward trend across the study period.




(a): Positive (b): Negative

Figure 5: Linear Trend Models for Positive and Negative Typhoid Cases


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Table 4: Linear Trend Model Coefficients

| Term | Positive Cases | Negative Cases |
|---|---|---|
| Intercept | 1081.48 | 1041.24 |
| Time (Slope) | -0.5026 | -0.5064 |

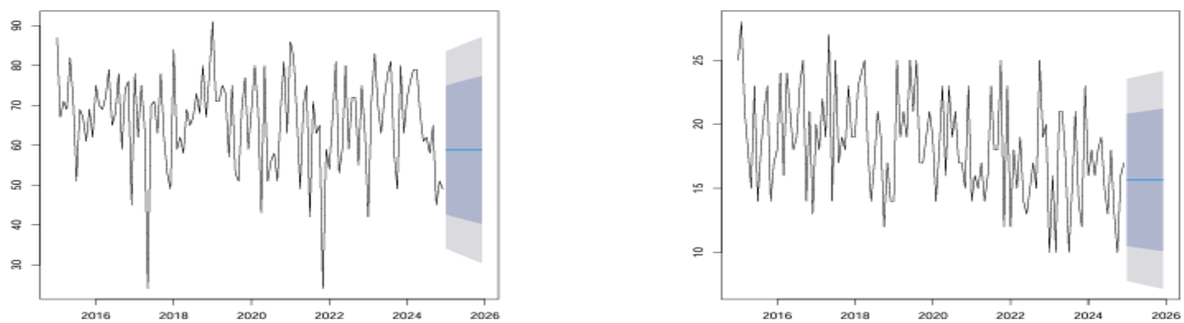
Figure 5 and Table 4 indicated a gradual decline in both positive and negative typhoid cases over the 10-year period. The negative slopes suggest a consistent downward trend, reflecting potential improvements in public health and disease control.

Forecasting Models

This section explores forecasting approaches including exponential smoothing, ARIMA, and Fourier series to project future typhoid trends and support early intervention planning.

**Exponential Smoothing Forecast**

Exponential smoothing models were employed to provide short-term forecasts by effectively capturing both trend and seasonality in the data. Figure 6 presents the predicted values for positive (a) and negative (b) typhoid cases.




(a): Positive (b): Negative

Figure 6: Exponential Smoothing Forecast: Positive and Negative Typhoid Cases

The forecasts in Figure 6 revealed a continuation of the slight downward trend observed in the historical series, accompanied by regular seasonal fluctuations. These results indicate that exponential smoothing effectively models the time-dependent structure of the data, supporting its suitability for short-term epidemiological projections.

**ARIMA Forecast and Diagnostics**

ARIMA models were selected based on performance metrics such as AIC and RMSE. Table 5 summarizes the ARIMA models fitted to the typhoid case series.


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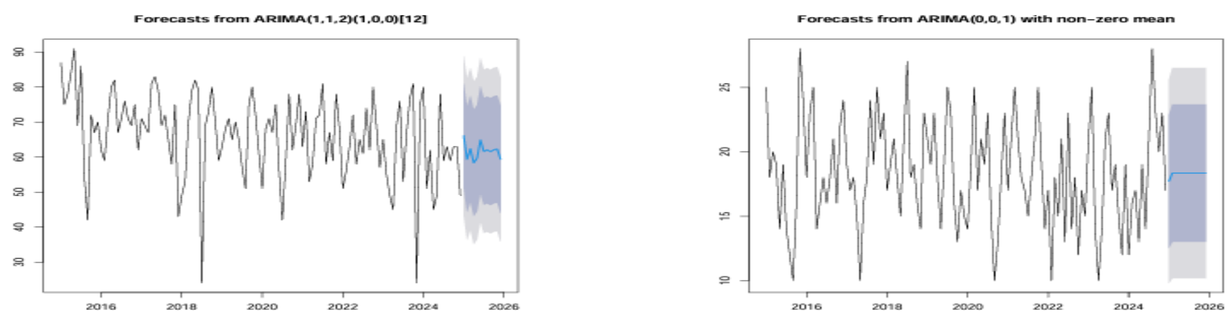
Table 5: ARIMA Model Summary

| | Positive Cases | Negative Cases |
|---|---|---|
| Model | ARIMA(0,0,0)(0,0,1)[12] | ARIMA(1,1,2)(0,0,1)[12] |
| Log Likelihood | -466.36 | -327.16 |
| AIC | 938.72 | 664.32 |
| RMSE | 11.78 | 3.72 |
| MAE | 9.19 | 3.10 |
| MAPE | 16.49% | 18.77% |

The selected models differ in complexity, with ARIMA(0,0,0)(0,0,1)[12] chosen for positive cases and ARIMA(1,1,2)(0,0,1)[12] for negative cases. Both models showed a good fit, with low RMSE and MAE values, and forecast accuracy, as indicated by MAPE, is acceptable for both series. The forecasts are displayed in Figure 7.




(a): Positive (b): Negative

Figure 7: ARIMA Forecast: Positive and Negative Typhoid Cases

Figure 7 showed the ARIMA-based forecasts for positive (a) and negative (b) typhoid cases. The forecast plots align well with historical trends and effectively capture seasonal fluctuations. The projected values suggest continued moderate variability and a stable or slightly declining trend, indicating that the ARIMA models provide reliable short-term predictions for both case categories.

Further confirmation of model adequacy is provided in Figure 8, which presents diagnostic checks, and Table 5, which details model characteristics. Together, these outputs support the validity of the ARIMA models for epidemiological forecasting in this context.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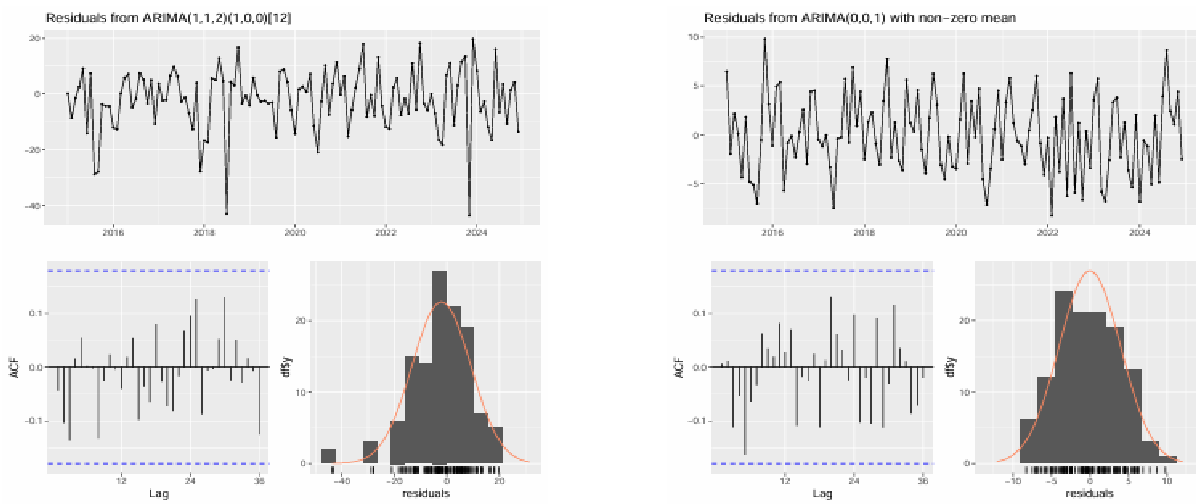


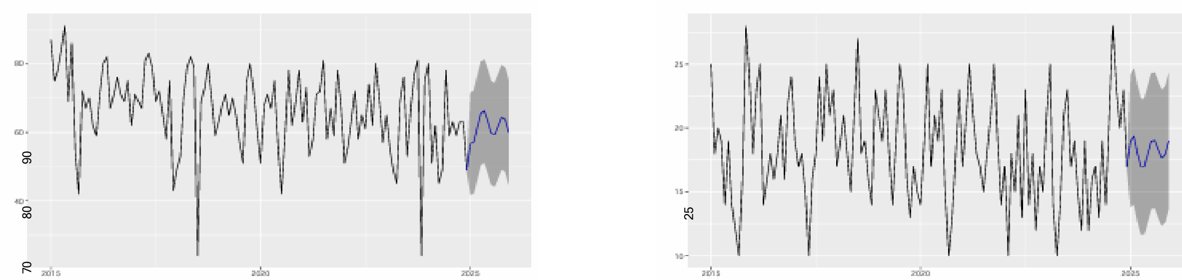
(a): Positive (b): Negative

Figure 8: ARIMA Model Diagnostics: Positive and Negative Typhoid Cases

Figure 8 showed diagnostics for ARIMA models fitted to monthly positive and negative typhoid cases at Grimard Catholic Hospital. Residuals for both series are randomly scattered around zero, with ACF and PACF plots indicating no significant autocorrelation, suggesting the models successfully capture trend and seasonality. Residuals approximate normality, validating forecast intervals. Overall, the ARIMA models are appropriate for short-term prediction, supporting early warning, resource allocation, and targeted public health interventions.

Fourier Series Forecast

Fourier terms were integrated to model complex seasonal patterns in the typhoid case data. Figure 9 displays the Fourier series forecasts for positive (a) and negative (b) typhoid cases. The models effectively capture both the underlying trends and smooth periodic behavior, accurately reflecting the recurring seasonal fluctuations observed in the data. The strong alignment between the observed and fitted values suggests that the Fourier series approach is a reliable and robust tool for modeling seasonal dynamics in typhoid case patterns.



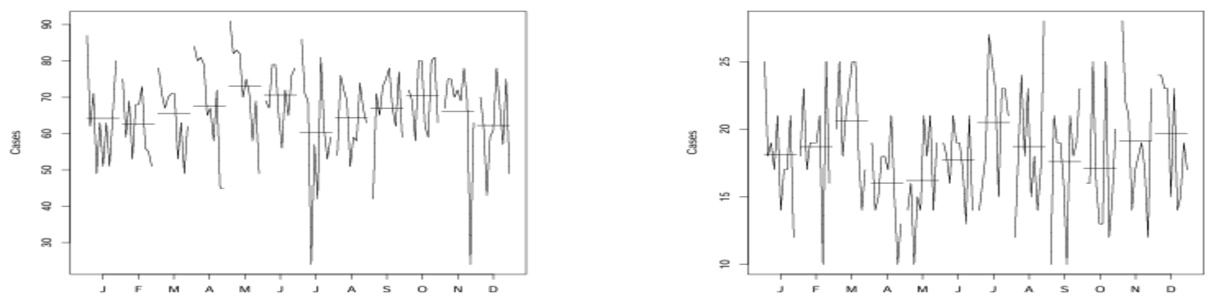
(a): Positive (b): Negative

Figure 9: Fourier Series Forecast: Positive and Negative Typhoid Cases

Figure 9 indicated Fourier Series forecasts capturing seasonal patterns in typhoid cases. Both positive and negative cases show cyclical fluctuations, reflecting strong periodic behaviour influencing future case patterns.

Seasonal Pattern Characterization

Figure 10 presents seasonal month plots for positive (a) and negative (b) typhoid cases. Both plots reveal recurring monthly patterns, indicating strong seasonality. Positive cases peak consistently during the rainy season months, while negative cases show relatively stable fluctuations. Notably, March and August stand out as months with consistently high case counts. These seasonal trends underscore the role of environmental and climatic conditions in typhoid prevalence and transmission dynamics, which are crucial considerations for public health planning.




(a): Positive (b): Negative

Figure 10: Seasonal Month Plot: Positive and Negative Typhoid Cases

Figure 10 showed the seasonal month plot of typhoid cases, highlighting recurring monthly patterns. Positive and negative cases exhibit clear seasonality, with peaks and troughs occurring consistently across the years.

**Discussion**

The results of this 10-year epidemiological study of typhoid fever cases at Grimard Catholic Hospital in Anyigba offer important new information about the disease's temporal dynamics. Improvements in sanitation, public health education, and disease surveillance have all contributed to a decrease in incidence rates in other sub-Saharan African regions, which is consistent with the observed downward trend in confirmed positive cases (Crump et al., 2004; Mogasale et al., 2014).

The data showed a clear seasonal trend, with typhoid case maxima often occurring during the rainy months, especially in March and August. This is in line with the well-established knowledge that water source contamination and improper waste disposal during times of heavy rains are directly linked to the spread of typhoid. Studies from Kenya, Ghana, and portions of India have shown similar seasonal variations, where rainfall patterns have a direct impact on population exposure to enteric pathogens and water quality (Bhutta, 2006; Buckle et al., 2012).

Linear regression and exponential smoothing models show a steady decrease in both positive and negative case counts, which probably reflects a mix of underlying improvements in the Dekina LGA's public health. These could include enhanced community awareness of typhoid symptoms, better access to drinkable water, better cleanliness habits, and a greater propensity to seek medical assistance right away. It is also conceivable that the expansion of healthcare infrastructure, enhanced diagnostic capabilities, and focused intervention campaigns, such as health outreach and immunisation initiatives, have contributed to a decrease in the burden of disease.

However, the data indicates that the population is still susceptible to sporadic outbreaks, with mild oscillations and sporadic peaks in case numbers. Environmental disasters like flooding, poor infrastructure maintenance, population shifts, or inconsistent preventive behaviour, especially during periods of high transmission, may be the cause of these. From a forecasting standpoint, trend and seasonal dynamics were successfully captured by using Fourier series models, exponential smoothing, and ARIMA. These models' short-term prediction accuracy highlights their potential use in early warning systems and real-time public health surveillance. Such modelling techniques could improve prompt decision-making, allow for more strategic resource deployment, and support community-level sensitisation initiatives when incorporated into regular monitoring frameworks.

Although the study offers a thorough evaluation, a number of limitations should be taken into account. First, the assessment of temporal trends may be biassed due to incomplete or underreported information in some months. Second, the shift from more antiquated techniques like the Widal test to more contemporary rapid diagnostic procedures may have caused variations in diagnostic consistency during the course of the study, which may have impacted comparability between years. Third, because the dataset is hospital-based, it mostly includes those who actively sought medical attention, potentially leaving out mild or asymptomatic instances treated outside of official healthcare channels. In order to overcome these constraints and improve typhoid monitoring in the future, community-level data collection methods should be strengthened in addition to hospital records. Data quality and comparability would also be enhanced by standardising diagnostic procedures amongst facilities. Additionally, ongoing community education can be a proactive strategy to lower the risk of transmission and outbreaks, especially before the rainy season.

## Conclusion

This study, which examines the dynamics and epidemiological patterns of typhoid fever in North-Central Nigeria, reveals notable seasonal and temporal fluctuations in the disease's frequency during a ten-year period at Grimard Catholic Hospital in Anyigba. Improvements in the region's public health conditions are suggested by an overall decrease in the number of positive and negative tests. The observed seasonal peaks highlight the influence of infrastructure and environmental factors on the dynamics of typhoid transmission, especially during the rainy season. Time series models that successfully caught these tendencies and generated trustworthy forecasts were Fourier series, exponential smoothing, and ARIMA. The significance of ongoing epidemiological surveillance and context-specific interventions throughout North-Central Nigeria is emphasised by these findings. Investments in water and sanitation infrastructure, regular disease surveillance, and community-based hygiene education are all crucial targeted efforts. Overall, the study shows that solid, data-driven studies are crucial for comprehending typhoid fever dynamics and directing localised public health planning in high-risk areas of Nigeria.

## Recommendations

1. In order to ensure prompt and accurate detection of typhoid cases, public health initiatives in Anyigba and other high-risk areas should be reinforced through community-level surveillance and standardised diagnostic techniques, according to this 10-year epidemiological research.
2. To lessen environmental pollution and stop transmission, investments in potable water, sanitation facilities, and focused hygiene education are crucial, particularly prior to the rainy season.
3. In order to support early warning and evidence-based interventions, strategic vaccination and outreach programs should give priority to high-risk populations found through seasonal and demographic analyses. They should also incorporate reliable forecasting models like ARIMA, exponential smoothing, and Fourier series into routine monitoring.
4. Typhoid fever incidence reductions in North-Central Nigeria will be sustained, readiness will be further improved, and resource allocation will be optimised with the use of continuous longitudinal research and rapid response measures during environmental vulnerability.

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