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A Statistical Evaluation of the Occurence of Meningitis in Takum, Taraba State, Nigeria

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Abstract

Meningitis remains a critical public health issue in Nigeria, particularly within the dry season when environmental factors such as low humidity and dust elevate transmission risks. Using historical incidence data from 2012 to 2021, this study utilizes the Autoregressive Integrated Moving Average (ARIMA) model estimate and predict the occurrence of meningitis occurrences. Findings frm the study revealed that the ARIMA(1,1,0) model emerged as the optimal fit, capturing the seasonal patterns and temporal trends in meningitis cases. This study recommends the integration of ARIMA-based forecasting into Nigeria's public health strategies to strengthen early warning systems, optimize resource deployment, and enable more proactive responses during high-risk periods.

Keywords: Meningitis, Prediction, Modelling, Estimation, ARIMA

INTRODUCTION

Meningitis remains a significant public health challenge worldwide, particularly in sub-Saharan Africa, where seasonal outbreaks of the disease are recurrent and often devastating. The World Health Organization (WHO) reports that approximately 1.2 million cases of bacterial meningitis occur globally each year, with the African meningitis belt, which includes Nigeria, bearing a disproportionate burden (WHO, 2023). In Nigeria, meningitis outbreaks pose serious risks to communities, frequently overwhelming healthcare systems and leading to severe socioeconomic impacts (Oluwole et al., 2022). Given these challenges, accurate modeling and prediction of meningitis outbreaks are essential for effective prevention and response strategies. Nigeria's meningitis season is often influenced by environmental factors such as dust, humidity, and temperature, as well as sociopolitical issues like limited healthcare resources and public health infrastructure (Adepoju, 2021). Meningitis epidemics in Nigeria, particularly those caused by Neisseria meningitidis, have resulted in high mortality and morbidity rates. Recent outbreaks have demonstrated the need for timely and effective responses, which rely heavily on the accurate forecasting of case occurrence (Saidu et al., 2022).

Time series models, such as the Autoregressive Integrated Moving Average (ARIMA) model, have proven effective in predicting the spread of infectious diseases by capturing temporal patterns in historical data (Zhou et al., 2023). The ARIMA model's ability to forecast trends based on past data makes it a valuable tool in the epidemiological analysis of diseases like meningitis, where seasonal and temporal fluctuations are critical (Wang et al., 2022). This model can facilitate targeted intervention strategies by predicting the timing and magnitude of meningitis outbreaks, which is particularly relevant in resource-limited settings like Nigeria. This study, therefore, seeks to develop an ARIMA-based statistical model for the occurrence of meningitis using data from Takum General Hospital, Taraba State, Nigeria.

Literature Review

Meningitis is a critical health issue in Nigeria, largely driven by the epidemiology of Neisseria meningitidis, environmental conditions, and socioeconomic factors. Located within the African meningitis belt, Nigeria experiences frequent outbreaks, particularly during the dry season from November to May. This seasonality is closely linked to the climatic conditions in the region, including low humidity and dusty winds, which create an environment that facilitates bacterial spread and transmission (WHO, 2023). Studies have shown that these conditions exacerbate mucosal dryness in the respiratory tract, increasing the likelihood of bacterial colonization and subsequent transmission (Adepoju, 2021).

The incidence of meningitis is also influenced by population density, socioeconomic status, and healthcare accessibility. In resource-limited settings like Nigeria, constrained access to healthcare resources and vaccines complicates early diagnosis and prevention efforts. This is compounded by public health infrastructure limitations, such as inconsistent data reporting and inadequate disease surveillance systems, which can hinder timely intervention (Saidu et al., 2022).

Empirical Review

Mathew and Idi (2024) conducted a study on the occurrence of typhoid fever in Takum, Taraba State, Nigeria using autoregressive integrated moving average (ARIMA) and a historical data covering a period covering 2012 to 2021 from the General Hospital Takum. Results from their study revealed that ARIMA (4,1,1) as the optimal model, selected through model evaluation metrics; Akaike Information Criterion (AIC), corrected AIC (AICC), and Bayesian Information Criterion (BIC). The study's findings further revealed an upward trend in typhoid fever cases over the forecast period, suggesting a continuing rise in disease incidence.

Adepoju (2021) conducted a study on the seasonal patterns and environmental determinants of meningitis outbreaks in Northern Nigeria. They utilized secondary data from the Nigerian Center for Disease Control (NCDC) covering the years 2010 to 2020. Employing regression analysis, Adepoju found that meningitis outbreaks significantly correlated with dry season conditions, including low humidity and high dust levels. The study concluded that environmental factors should be integrated into meningitis prevention strategies and recommended that vaccination campaigns be intensified in high-risk months to prevent outbreaks.

Oluwole et al. (2022) studied the incidence cholera in Lagos State based on time series data from the Lagos State Ministry of Health, spanning 2015 to 2020. The researchers used the ARIMA model for data analysis, finding that the model provided accurate short-term forecasts for cholera cases. They concluded that ARIMA models are useful for anticipating infectious disease trends in Lagos and recommended that public health authorities consider adopting time series models to guide resource allocation for outbreak responses.

Nwankwo and Okoli (2023) undertook a study on the prevalence of malaria in rural Nigerian communities, using from local health records covering 2012 to 2022. The researchers used ARIMA to model seasonal trends in malaria incidence, finding that the model successfully captured peaks in transmission during the rainy season. They concluded that ARIMA modeling is effective for forecasting malaria and suggested that preemptive intervention strategies be implemented to manage expected seasonal increases.

Zhou et al. (2023) examined tuberculosis trends in China, with data collected from the China Health Statistics Database covering 2005 to 2021. The researchers applied ARIMA analysis, which revealed a consistent pattern of tuberculosis incidence over time, enabling accurate trend predictions. Zhou et al. concluded that ARIMA is a valuable tool for infectious disease forecasting and recommended its adoption for early warning systems in tuberculosis control.

Wang et al. (2022), in their study on forecasting dengue fever cases in Southeast Asia utilized time series data from the Southeast Asia Regional Disease Surveillance Network, covering the years 2010 to 2020. Their findings, derived from ARIMA modeling, showed that the model accurately predicted seasonal peaks in dengue incidence. The researchers concluded that ARIMA models offer practical forecasting insights and recommended them as part of a comprehensive strategy for managing dengue outbreaks.

Saidu et al. (2022) conducted research on environmental and socioeconomic drivers of meningitis outbreaks in Nigeria, focusing on how socioeconomic and environmental factors contribute to the frequency of meningitis cases. Using data from the NCDC spanning 2011 to 2021, they applied multiple regression analysis to reveal that both environmental and socioeconomic variables significantly affected meningitis prevalence. They concluded that socioeconomic factors play a vital role in disease outbreaks and recommended that health policies address socioeconomic disparities to reduce meningitis risk.

Akobi and Ogunmola (2024) conducted a study on Application of ARIMA Methods on Unemployment and Inflation Rates in Nigeria, addressing the challenges of economic instability caused by high unemployment and inflation rates. Utilizing secondary data from the National Bureau of Statistics (NBS) from 1991 to 2020. After evaluating multiple ARIMA models, they identified ARIMA(0,1,1) as the most suitable model for both unemployment and inflation series, based on criteria like the (AIC) and (BIC). The study's findings revealed that both unemployment and inflation rates in Nigeria would maintain relatively constant levels over the forecast period. Diagnostic checks confirmed the model's adequacy, with residual analyses showing no significant autocorrelation or heteroscedasticity. They recommended that policymakers implement targeted interventions to reduce these rates and enhance economic stability.

Aliyu et al. (2020) explored predictive modeling of lassa fever working with data from the Nigerian Ministry of Health from 2008 to 2019. Using ARIMA models, Aliyu et al. found that the model could predict Lassa fever case trends accurately. The study concluded that ARIMA is a reliable tool for forecasting infectious disease outbreaks in Nigeria and recommended its application to other diseases with seasonal patterns, including meningitis.

Chen et al. (2021) caried out a study on the application of ARIMA Models in Influenza Forecasting, using influenza case data from the World Health Organization (WHO) for the years 2000 to 2020. Their study found that the model successfully captured influenza seasonality, allowing for effective short-term forecasting. The study concluded that ARIMA is beneficial for predicting infectious disease patterns and recommended its integration into national influenza monitoring systems for early warning purposes.

Adeyemi and Lawal (2023) studied cholera outbreaks in West Africa using time series data from the West African Health Organization from 2013 to 2022. Using ARIMA models, they identified a significant cyclical pattern in cholera cases, particularly during rainy seasons. The researchers concluded that time series analysis provides valuable predictive insights and recommended that governments use this information to pre-position resources before outbreak peaks.

Kassim and Bello (2022) examined the role of ARIMA Models in Forecasting Malaria Trends in Sub-Saharan Africa, using data from the African Health Observatory for the period from 2005 to 2021. Their study revealed strong seasonal trends in malaria transmission, which the researchers attributed to seasonal climate variations. They concluded that ARIMA models are effective in capturing malaria's seasonality and recommended the model's broader application in other infectious diseases in Africa to improve health intervention planning.

METHODS

Method of Data Collection

For this study, a quantitative research design was adopted. Data for this research were sourced from the General Hospital Takum, for a period of 9 years, from 2012 to 2021. Time series analysis, methods were adopted for the analysis. To understand and visualize some hidden characteristics of the series, consider the following equation:

$$Z_t = T_t + S_t + C_t + I_t \tag{1}$$

where: Z_t is the time series, T_t is the trend component, S_t is the seasonal component, C_t is the cyclical component, I_t is the irregular component.

Model Identification

The model identification process begins with examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots help in determining the initial values for the ARIMA (*p, d, q*) model parameters (Box & Jenkins,1970). To ensure the time series is stationary, we perform unit root tests such as the Augmented Dickey-Fuller (ADF) test. The ADF test checks for the presence of a unit root:

$$\Delta Z_t = \alpha + \beta_t + \gamma Z_{t-1} + \delta \sum_{i=1}^{p} \Delta Z_{t-1} + \grave{O}_t \tag{2}$$

where: ΔZ_t is the differenced series, α is a constant, β_t is the coefficient on a time trend, γ is the coefficient on the lagged level of the series, $\grave{O}_t$ is the error term (Dickey & Fuller, 1979).

Autocorrelation Function (ACF) and **Partial Autocorrelation Function (PACF)**: After differencing, the ACF and PACF are analyzed to determine the appropriate orders (*p*) and (*q*) of the ARIMA model.

The ACF is defined as:

$$\text{ACF}(k) = \frac{\sum_{t=k+1}^{n} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n} (Y_t - \bar{Y})^2} \tag{3}$$

The PACF can be calculated using the formula:

$$\text{PACF}(k) = \text{ACF}(k) - \sum_{j=1}^{k-1} \text{PACF}(j) \cdot \text{ACF}(k-j) \quad (4)$$

Identifying the ARIMA Model: Based on the ACF and PACF plots, the orders (*p*) and (*q*) are selected. For example:

- If the PACF cuts off after lag (*p*) and the ACF tails off, an AR(*p*) model is suggested.
- If the ACF cuts off after lag (*q*) and the PACF tails off, an MA(*q*) model is suggested.
- If both ACF and PACF tail off, an ARMA (*p, q*) model may be appropriate.

Estimation of Model Parameters

Once the appropriate ARIMA (*p, d, q*) model is identified, parameters are estimated using methods like maximum likelihood estimation.

Model Estimation

The general form of the ARIMA model can be represented as:

$$\phi(B)(1-B^d)Y_t = \theta(B)\varepsilon_t \quad (5)$$

where: $(\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)$ (the AR part); $(\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q)$ (the MA part); (B) is the backshift operator defined as ($B\ Y_t\ =\ Y_{t-1}$); (ε_t) is white noise.

Parameter Estimation: Parameters (ϕ_i) and (θ_j) can be estimated using maximum likelihood estimation or the method of moments. The likelihood function (*L*) for the ARIMA model is given by:

$$L(\phi, \theta) = \prod_{t=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\varepsilon_t^2}{2\sigma^2}\right) \quad (6)$$

where (σ^2) is the variance of the residuals

Model selection criteria such as the Akaike Information Criterion (AIC), corrected AIC (AICC), and Bayesian Information Criterion (BIC) are used:

$$AIC = -2\ln(L) + 2k \quad (7)$$

$$AICc = AIC + \frac{2k(K+1)}{n-k-1} \tag{8}$$

$$BIC = -2\ln(L) + k\ln(n) \tag{9}$$

where L is the likelihood of the model, k is the number of parameters, and n is the number of observations (Anderson, 2002).

Diagnostic Checking for the Fitted Model

Diagnostic checks ensure the model's adequacy. The Box-Ljung test for serial correlation is given by:

$$Q = n(n+2)\sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{n-k} \tag{10}$$

where n is the number of observations, $\hat{\rho}_k$ is the sample autocorrelation at lag k, and m is the number of lags (Box & Pierce, 1970).

The Shapiro-Wilk test for normality of residuals uses

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(t)}\right)^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{11}$$

where x_i are ordered sample values and ia are constants (Shapiro & Wilk, 1965).

The ARCH-LM test for heteroscedasticity involves regressing the squared residuals on lagged squared residuals and checking the significance of the regression (Engle, 1982).

Model Forecast

The fitted model is used to forecast the future occurrence of malaria and typhoid fever. The forecast estimation function for h periods ahead is:

$$\hat{Z}_{t+h/t} = \mu + \sum_{i=1}^{p} \phi_i Z_{t+h-i} + \sum_{i=1}^{p} \theta_j \grave{O}_{t+h-j} \tag{12}$$

where μ is the mean, ϕ_i and θ_j are model parameters, and $\grave{O}_t$ is the error term (Hyndman & Athanasopoulos, 2018).

RESULTS

Descriptive Statistics

Table 1 shows that the average number of Meningitis cases is 50679, with a standard deviation of 5099, indicating moderate variability. The skewness of -0.30 suggests a slight left skew, and the kurtosis of -0.59 indicates a nearly normal distribution. This suggests a fairly consistent pattern in the number of Meningitis cases over the observed period.

Table 1: Descriptive statistics for Meningitis series

	Sample size	Mean	Median	Standard deviation	Skewness	Kurtosis
Meningitis	30	50679	51856	5099	-0.30	-0.59

Graphical Presentation of the Data

The time series plot in Figure 1 illustrates the incidence of typhoid fever over the study period. This plot shows the number of Meningitis cases on the Y-axis against equally spaced time intervals (Year) on the X-axis. It is used to evaluate the patterns and trends in the meningitis series.

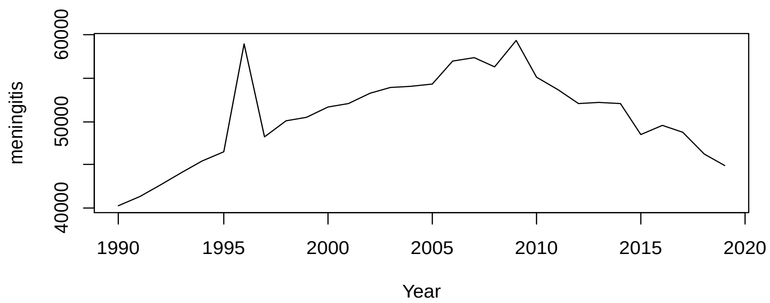

Figure 1: Time series plot for the meningitis series.

The plot above clearly indicates an upward trend in the typhoid fever series from 2012 to 2021. The possible influences in the series are examined using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.

Model Identification

The model identification process is crucial for fitting an Autoregressive Integrated Moving Average (ARIMA) model to the typhoid fever series. Before selecting a suitable model, the series must exhibit stationarity. Stationarity is checked using the sample ACF and PACF plots, the Augmented Dickey-Fuller (ADF) test. A stationary series will have an ACF that rapidly decays to near zero, while a non-stationary series will show lag spikes that slowly decay. The PACF of a stationary series will display only a few significant lag spikes. Figure 2 shows the ACF and PACF plots of the data series. A critical look at these plots reveals that the data series is non-stationary.

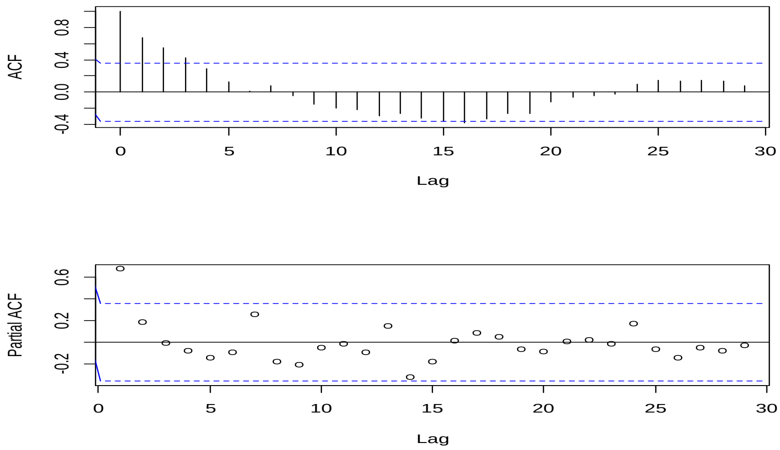

Figure 2: ACF and PACF plots for the Meningitis series.

Unit Root Test for Meningitis Series

The stationarity test result using ADF test is presented in Table 2. The results revealed that the ADF test fails to reject the null hypothesis of a unit root, with a test statistic of -0.84093 ($P > 0.05$) at the 5% significance level. These results indicate that the Meningitis series is non-stationary and requires differencing or transformation to achieve stationarity.

Table 2: Stationarity test for Meningitis

Series	**Augmented dickey fuller ADF test**		
Variable	**Test statistic**	**P-value**	**Remarks**
Meningitis	-0.84093	0.9456	Non stationary

Differenced Meningitis

The Meningitis series was identified as non-stationary based on preliminary tests conducted on the original data. To achieve stationarity, the series was differenced once with respect to trend. Figure 3 displays the graphical plot of the first-order differenced Meningitis series, which illustrates the series after this transformation.

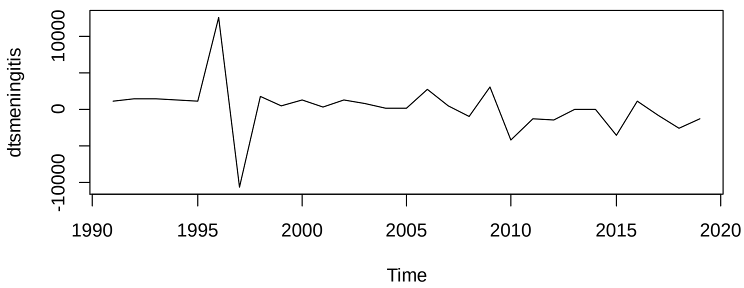

Figure 3. Time plot for the differenced Meningitis series

The differenced series depicted in Figure 3 with the superimposed line as the mean shows that the mean, variance and auto-covariance are constant over time, expressing series stationarity. The ACF and PACF plots, the ADF unit root tests are performed to augment the graphical presentation of the differenced series. The correlogram plots in Figure 5 shows only a few significance lag spikes which depicts a stationary series.

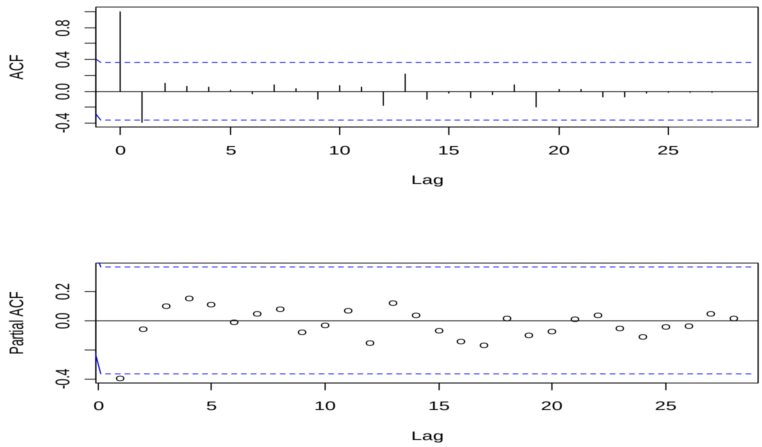

Figure 4: ACF and PACF plot for the second order differenced Meningitis series

The unit root test results for the first-order differenced Meningitis series are presented in Table 4. The ADF test produced a statistic of -3.4953, with a p-value less than 0.05, leading to the rejection of the null hypothesis of a unit root. These results confirm that the differenced Meningitis series is stationary and suitable for modeling using the Box-Jenkins (ARIMA) methodology

Table 3. ADF test for the differenced Meningitis series

Series	**Augmented dickey fuller ADF test**		
Variable	**Test statistic**	**P-value**	**Remarks**
Meningitis	-3.4953	0.01305	Stationary

Estimation of Model Parameters

The differenced Meningitis series plot after the series is proven to be stationary is used to identify the appropriate model for this study. Based on the selection criteria, the ARIMA (1,1,0) model was identified as the best fit, representing an integration of order 1 (I(1)) and a moving average component of order 1 (MA(1)). Table 4 presents the model selection statistics, including the Akaike Information Criterion (AIC), the corrected Akaike Information Criterion (AICC), and the Bayesian Information Criterion (BIC). The ARIMA (1,1,0) model is preferred as its penalty statistics are lower compared to alternative models, with (***) denoting it as the best fit according to these criteria.

Table 4: Tentative ARIMA models for the meningitis series

Model	AIC	AICc	BIC	Likelihood
ARIMA (2,1,2)	560.75	564.57	568.96	-274.38
ARIMA (0,1,0)	559.11	559.57	561.84	-277.55
ARIMA (1,1,0)*	**556.37**	**557.33**	**560.47**	**-275.19**
ARIMA (0,1,1)	556.87	557.83	560.97	-275.43
ARIMA (2,1,0)	558.24	559.91	563.71	-275.12
ARIMA (1,1,1)	558.29	559.95	563.76	-275.14
ARIMA (2,2,1)	560.19	562.8	567.02	-275.09

Model Parameter Estimates

From Table 5, the estimates for both the AR (1) components of the ARIMA (1,1,0) model are statistically significant, with t-values exceeding two, indicating their importance in the model. The estimated coefficients fall within the required bounds for stationarity and invertibility, as they lie between -1 and 1. Therefore, the chosen model, based on the principle of parsimony, is:

$$\hat{y}_t = \delta_t + 0.3828 y_{t-1} \quad (13)$$

This model effectively captures the dynamics of the Meningitis series while adhering to the criteria for model stability and simplicity.

Table 5: Model Fit Statistics For meningitis series

Coefficient	Estimate	Std Error	t-value	$P(>\|t\|)$
AR (1)	0.3828	0.1677	2.282648	0.0224

Post-Estimation Analysis Fitted Model

The model parameters have been estimated using maximum likelihood estimation technique and also found to be significant. This assessment involves several diagnostic checks. Correlogram plots of the residuals are examined to identify any remaining autocorrelation, while the Box-Ljung test is used to ensure the residuals are white noise and do not exhibit serial correlation. The Shapiro-Wilk test is conducted to verify that the residuals are normally distributed, and the ARCH-LM test is employed to detect any heteroscedasticity by analyzing the presence of volatility clustering in the squared residuals. The results of these diagnostic checks, presented in Figure 5, showed that the model is well-suited for accurate predictions.

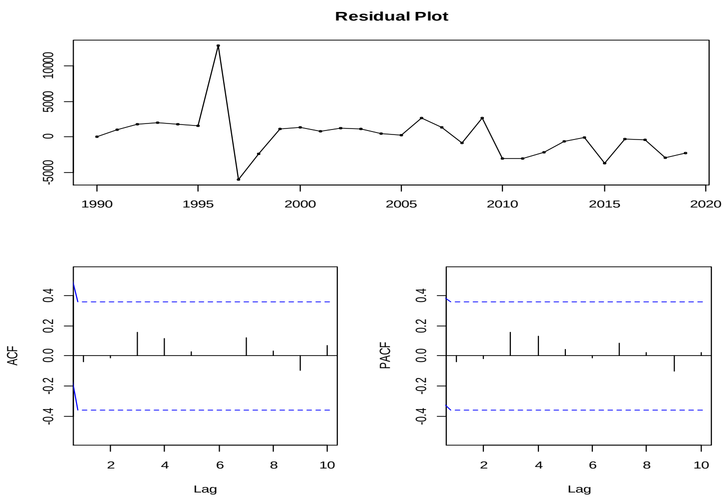

Figure 5: Residual plots for the meningitis series

Table 6 presents the results of several diagnostic tests used to evaluate the adequacy of the fitted model. The Box-Ljung test, with a chi-square statistic of 6.0897 and a p-value of 0.9782, indicates that there is no significant autocorrelation in the residuals, suggesting that the residuals are independently distributed. Lastly, the Shapiro-Wilk test, with a W statistic of 0.81394 and a p-value of 0.00019, indicates that the residuals are not normally distributed and therefore needs to be transformed.

Table 6: Box-Ljung test

Test Type	Chi-Square	Df	P – Value
Ljung-Box	6.0897	15	0.9782

Table 7: Shapiro-Wilk Test Statistics

Shapiro-Wilk	**Wilks's value**	**p-value**
	0.81394	0.00019

Model Forecast

Forecasting is a primary goal of model building. In this study, the forecast estimation for h periods ahead is given by:

$$\hat{y}_{T+h/T} = \theta_t \delta_{T+h-1/T} \tag{14}$$

Where $\hat{y}_{T+h/T}$ represents the forecasted value and $\theta_t \delta_{T+h-1/T}$ is the forecast error from the previous period. The forecast error $\hat{\delta}_t(h)$ is calculated as

$$\hat{\delta}_t(h) = \hat{y}_{T+h/T} - \theta_t \delta_{T+h-1/T} \tag{15}$$

With $\hat{y}_{T+h}$ being the actual Meningitis value at $(T + h)$. Given that the model has passed all diagnostic tests, it is employed to forecast future Typhoid Fever cases. The forecast values for the twenty-four months spanning 2012 to 2021 are detailed in Table 7, and the forecast plot is illustrated in Figure 6.

Table 8. ARIMA forecast for the meningitis

Forecast for the meningitis series

Year	Forecast	95% lower CI	95% upper CI
2020	45401.36	39023.67	51779.05
2021	45216.38	37710.89	52721.86
2022	45286.59	36336.43	54236.75

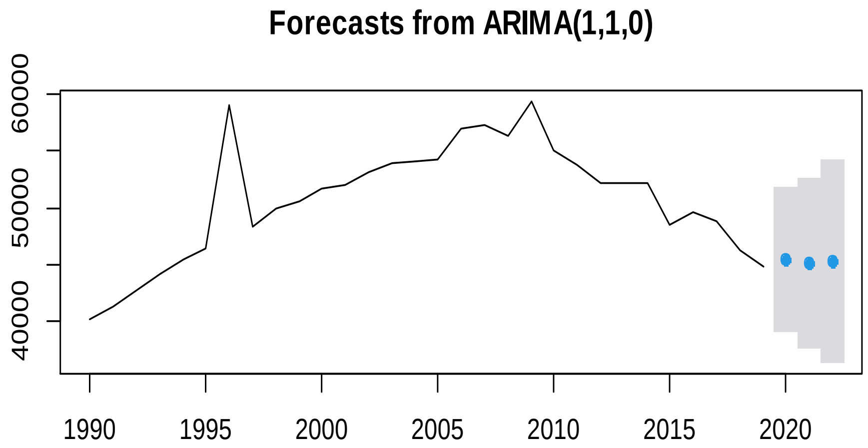

Figure 6: Plot for meningitis series including 3 years forecast

DISCUSSION

The findings of this study reinforce the efficacy of the ARIMA model in forecasting seasonal diseases, specifically meningitis in Nigeria. Using Nigerian health data, the study identified that an ARIMA(1,1,0) model best captured the time series trends in meningitis cases, providing reliable forecasts. This outcome aligns with prior studies, such as Oluwole et al. (2022) on cholera in Lagos State and Zhou et al. (2023) on tuberculosis in China, both of which highlighted the ARIMA model's effectiveness in forecasting diseases with marked seasonal and temporal patterns. By enabling accurate short-term predictions, ARIMA models are shown to be highly adaptable for infectious disease forecasting, even within resource-limited settings.

Additionally, this study's findings confirmed the relationship between seasonal environmental factors and meningitis prevalence in Nigeria, consistent with research by Adepoju (2021), which demonstrated how dry season conditions—characterized by low humidity and dust—heighten disease transmission risks. The model's ability to capture these seasonal peaks underscores ARIMA's suitability for epidemiological analysis in areas where environmental influences are pronounced. This study thereby corroborates existing literature while uniquely focusing on meningitis, a disease that has received comparatively limited attention in ARIMA modeling within Nigeria. The results suggest that ARIMA forecasting can play a critical role in planning health interventions and timely resource distribution for meningitis outbreaks.

CONCLUSION

This study concludes that the ARIMA (1,1,0) model is an effective predictive tool for meningitis in Nigeria, capturing seasonality and temporal patterns in incidence data with significant accuracy. The use of Nigerian health data validates the ARIMA model's utility in forecasting disease trends within this regional context, underscoring its practical value for public health preparedness. The results support ARIMA's application as a vital component in Nigeria's public health strategy, especially for diseases like meningitis that exhibit seasonal surges. Reliable forecasting based on the ARIMA model can enhance proactive responses, reduce morbidity, and facilitate efficient resource allocation.

Recommendations

Based on the result of this study, the following recommendations are proposed:

i. Nigerian health authorities should incorporate ARIMA models in epidemiological surveillance systems to improve early warning and response capabilities for meningitis and other seasonal diseases.

ii. Improving data collection processes and ensuring high-quality, continuous data is essential for refining the model's accuracy and reliability. This may involve strengthening health information systems at both national and regional levels.

iii. Vaccination efforts should be strategically scheduled in line with the ARIMA model's predicted periods of high meningitis incidence, particularly during the dry season.

iv. Public health resources, including medical supplies and personnel, should be pre-positioned in regions anticipated to experience meningitis peaks, enhancing the efficiency and timeliness of outbreak responses.

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