MIKAILALSYS
Journal of Multidisciplinary Sciences

e-ISSN : 2987-2286
p-ISSN : 2987-3924

Index : Dimensions, Scilit, Crossref, Garuda, Semantic, Lens,Google Scholar,Base, etc

https://doi.org/10.58578/mikailalsys.v3i2.6366

Comparing Univariate Time Series Forecast Methods for Malaria Fever Cases

Adeniyi Oyewole Ogunmola & Yunusa Namale Jibo
Federal University Wukari, Taraba State, Nigeria.
ogunmola@fuwukari.edu.ng; yunusajibon@gmail.com

Article Info:

Submitted:	Revised:	Accepted:	Published:
May 23, 2025	Jun 21, 2025	Jul 3, 2025	Jul 8, 2025

Abstract

This study evaluates the forecasting accuracy of three univariate time series models, Decomposition, Holt-Winter's, and Seasonal Autoregressive Integrated Moving Average (SARIMA) for predicting monthly malaria fever cases from January 2008 to December 2024. Data were obtained from the Federal Medical Centre, Jalingo, and analyzed using the three models. Forecasting performance was assessed using Root Mean Square Error (RMSE) as the primary evaluation metric. Among the models, the SARIMA (0, 0, 1) × (1, 1, 2) demonstrated the lowest RMSE, indicating superior forecasting accuracy over the Decomposition and Holt-Winter's methods. Seasonal trend analysis revealed that malaria fever cases tend to be higher from April to August, with June showing the highest seasonal index representing a 92% increase over the annual average. These findings highlight the SARIMA model's effectiveness in capturing the seasonal patterns of malaria incidence and its utility for public health planning and intervention.

Keywords: Malaria Fever; Time Series Analysis; Decomposition Method; Holt-Winter's Method; SARIMA Model; Forecast Accuracy

INTRODUCTION

Malaria remains one of the most serious public health challenges in many tropical and subtropical regions of the world, particularly in sub-Saharan Africa and parts of Asia and South America (CDC, 2024). Despite ongoing efforts to control and eradicate the disease, it continues to cause significant morbidity and mortality, especially among children and pregnant women (Schantz-Dunn and Nour, 2009; WHO 2024). Accurate forecasting of malaria incidence plays a critical role in enabling timely interventions, resource allocation, and policy planning. By anticipating future trends, public health authorities can better manage outbreaks, improve prevention strategies, and reduce the burden of the disease.

It is known that malaria transmission is driven by a complex interplay of factors from environmental, biological and sociological (Rudasingwa and Cho, 2024). These include temperature, rainfall, humidity, and population movement, all of which exhibit temporal patterns that can be captured using time series models. Statistical forecasting methods offer a valuable approach to modeling these patterns and predicting future incidence of malaria fever (Anwar et al., 2016; Ashraf et al., 2024). Among the various time series techniques, decomposition methods, Holt-Winters exponential smoothing, and Seasonal Autoregressive Integrated Moving Average (SARIMA) models have demonstrated effectiveness in handling seasonal and trend components inherent in epidemiological data.

The decomposition method enables the separation of a time series into its constituent components—trend, seasonality, and residuals—providing insights into the underlying structure of malaria incidence over time (Thomas et al., 2021; Soni A, 2024; Das and Barman, 2025). Holt-Winters exponential smoothing extends this by capturing both trend and seasonality adaptively, making it particularly suited for data with consistent seasonal patterns (Lee, 2025a; Ferbar and Strmcnik, 2016; and Lee, 2025b). Meanwhile, the SARIMA model provides a more flexible framework by incorporating autoregressive, moving average, and seasonal differencing components, making it capable of modeling more complex temporal dynamics (Ayiah-Mensah et al., 2025; Majka, 2024; Kwarteng and Andreevich, 2024).

This study aims to evaluate and compare the effectiveness of decomposition, Holt-Winters, and SARIMA models in forecasting malaria fever cases. Using historical malaria incidence data, we assess the predictive performance of each method and highlight their respective strengths and limitations. The findings are expected to contribute to the body of knowledge on time series forecasting in public health and support the development of early warning systems for malaria outbreaks.

MATERIALS AND METHODS

The study area of this research is Jalingo. Jalingo is the capital of Taraba State located in the northeastern region of Nigeria. Its population is 220,700 in an area of 401.2 kilometer, with a population density of 550.1 kilometer square (CP, 2022).

The data used in this study is secondary data on monthly number of malaria fever cases collected from Federal Medical Centre (F.M.C) Jalingo Taraba State, from January 2008 to December 2024. Three univariate time series methods of forecasting were fitted to the data.

The first method of forecasting is the decomposition method. Traditionally, the time series denoted as Y_t, is decomposed into its four components which are trend (T_t), cyclical (C_t), seasonal (S_t) and irregular (I_t) (Pollock, 1993). The decomposition can be either in additive form or multiplicative form given in equations (1) and (2) respectively.

$$Y_t = T_t + C_t + S_t + I_t \quad (1)$$

$$Y_t = T_t \times C_t \times S_t \times I_t \quad (2)$$

Generally, two distinct purposes for applying the decomposition method are to give a summary decomposition of the salient features of the time series, and to predict future values of a particular time series data. With much success and accuracy, this method is commonly used for short term forecasting (Cooray, 2008).

The second method is Holt-winters seasonal exponential smoothing. This is a little advance than the decomposition method. It is iterative process in smoothening using combinations of weights. The combination that produces the smallest MAPE, MAD or MSD is the optimal set of weights. In this method, the following must be estimated: the average level, the slope component and the seasonal component of the time series. The method accounts for some error in the forecast by its updating procedure (Adenomon and Ojehomon, 2014; Adenomon et al., 2014).

Equations of the method are given in equations (3) to (6) as;

(i) to update the level (a) or average level of the series,

$$a_t = \alpha\left[\frac{y_t}{S_i(t-1)}\right] + (1-\alpha)(a_{t-1} + b_{t-1}) \quad (3)$$

(ii) to update the slope (b),

$$b_t = \beta\,(a_t - a_{t-1}) + (1-\beta)b_{t-1} \quad (4)$$

(iii) to update the seasonal component (S_i),

$$S_{i(t+1)} = \gamma\left[\frac{y_t}{a_t}\right] + (1-\gamma)S_{it}\,(t-L) \quad (5)$$

(iv) to obtain, a one step ahead forecast

$$\hat{y}_{t+1}\,(t) = (a_{t-1} + b_{t-1})S_{it+1}(t+1-L) \quad (6)$$

where,

α = smoothing constant for level ($0<\alpha<1$);

β = smoothing constant for trend estimate ($0<\beta<1$);

γ = smoothing constant for trend estimate ($0<\gamma<1$);

L = length of seasonality.

The third method is seasonal autoregressive integrated moving average (SARIMA) process. The SARIMA model was developed from seasonal AR (Autoregressive) and seasonal MA (Moving Average) models. That is, incorporating the seasonal factor into the ARIMA model produces the SARIMA model (Box-Jenkins 1976). The model is represented in equation (7) as,

$$\text{SARIMA}\ (p, d, q) \times (P, D, Q)s \quad (7)$$

where, p, d, q, are the non-seasonal part and P, D, Q for the seasonal part.

The multiplicative seasonal ARIMA model is given in equation (8) as,

$$\Phi_p(B^s)\varphi_p(1-B)^d\,Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (8)$$

Where, s = 12 for monthly data and s = 4 for quarterly data (Cooray, 2008).

The following measures of accuracies used in the study for selecting the best model, and then method are:

Mean Absolute Error or Deviation (MAE or MAD)

The formular of MAD is given as

MAD $= \frac{\sum_{i=1}^{n}|e_i|}{n}$, where e_i is the ith error which measures the deviations from the series in absolute terms. Based on the absolute term, a measure of deviation is regarded as positive whether it is positive or negative. This measure tells us how much our forecast is biased. This measure is one of the most common used for analyzing the quality of different forecasts.

Mean Absolute Percentage Error (MAPE): measures the accuracy of fitted time series values. It is expressed as a percentage given as

$$\text{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{e_t}{x_t}\right|}{n} \times 100.$$

Mean Squared Deviation (MSD): This measure is computed using the same denominator, n, regardless of the model. So, one can compare MSD values across models. It is given by

$$\text{MSD} = \frac{\sum_{i=1}^{n}|e_t|^2}{n}.$$

In summary, for all the three measures the smaller the value, the better the fit of the model (Cooray, 2008).

Root Mean Square Error (RMSE): This measure is used to gauge the difference between the forecast from Decomposition, Winters' seasonal, and Seasonal Autoregressive Integrated Moving Average (SARIMA) method, and the actual data (Robertson and Tallman, 1999). The method with the minimum RMSE will emerge as the best method. The RMSE is given as;

RMSE $= \sqrt{\frac{\sum(y_t - \hat{y}_t)^2}{T}}$, where y_t is the actual time series, $\hat{y}_t$ is the time series data resulting from the forecast, and T is the length of the forecast period.

RESULTS

Descriptive statistics for malaria fever cases is presented in Table 1.

Table 1: Descriptive Statistics for Malaria Fever Cases

Variable	Mean	Median	Std Dev	Skewness	Kurtosis	Minimum	Maximum	N
Malaria	176.22	148	111.53	0.82	-0.11	21	148	192

The sample data contain 192 total months (January 2008 to December 2024). Descriptively the mean monthly cases of malaria fever (176.22) are greater than the mean monthly cases of typhoid fever (29.95) by a difference of 146.27. Also, the standard deviation of monthly malaria fever cases (111.53) is greater than the monthly typhoid fever cases (4.05) by a difference of 107.48 which is much. This tells us that the monthly reported malaria fever cases are far from being uniform, compare to the monthly reported typhoid fever cases. Descriptively, the monthly median of malaria fever cases (148) is greater than the monthly median of typhoid fever cases (30) by a difference of 18, the malaria fever cases is positively skewed with a magnitude of (0.82),

Figure 1 shows the malaria fever cases time series plot for the 192 months.

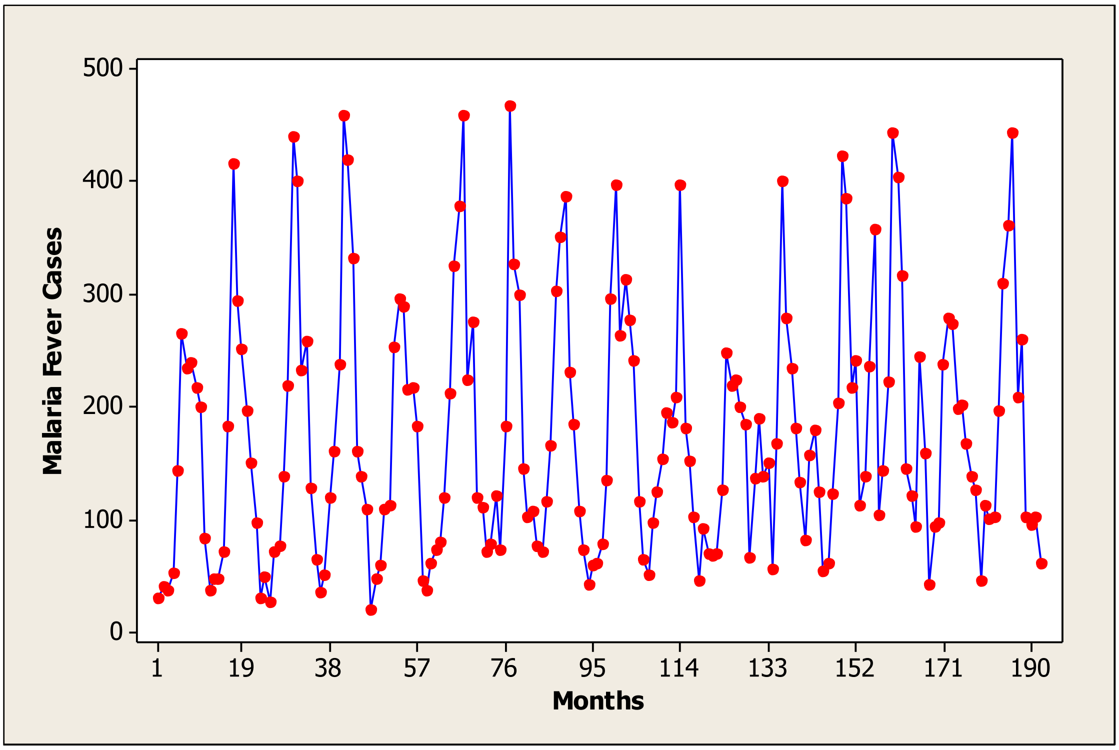

Figure 1: Time Series Plot for Malaria Fever Cases

The Figure 1 shows 16 cycles with 16 different peaks, this shows a seasonal variation in the time series plot, each cycle occurs within a year. Generally, there is no obvious trend going upward or coming downward in the time series plot.

Multiplicative model of Decomposition method of Forecasting:

Table 2 shows fitted trend equation derived from the fitted decomposition method.

Table 2: Decomposition Forecasting of Fitted Trend Equation

	Fitted Trend Equation
Malaria Fever	$Y_t = 147.1 + 0.391*t$

Table 2 shows the estimated fitted trend equation of malaria and typhoid fever cases from decomposition method. The linear trend equation for malaria fever cases shows that when time increases by a month, the malaria fever cases will also increase by 0.391.

Table 3: Seasonal Indices of Overall Malaria Fever Cases

Period	Malaria Fever Index	Percentage (%) index	Remarks
January	0.44490	44.490	Decrease by 55.510
February	0.58209	58.209	Decrease by 41.791
March	0.96347	96.347	Decrease by 3.653
April	1.63406	163.406	Increase by 63.406
May	1.79410	179.410	Increase by 79.410
June	1.92027	192.027	Increase by 92.027
July	1.41235	141.235	Increase by 41.235
August	1.12397	112.397	Increase by 12.397
September	0.73556	73.556	Decrease by 26.444
October	0.61590	61.590	Decrease by 38.410
November	0.38288	38.288	Decrease by 61.712
December	0.39045	39.045	Decrease by 60.955

Table 3 shows the estimated monthly indices of malaria fever cases. Expressing the indices in percentage, the month of April to August shows higher malaria fever cases than the annual percentage. The highest cases are in the month of June accounting for 92% increase over the annual. While the month of January to March and September to December experienced lower malaria fever cases than the annual. The lowest cases are in the month of November representing 61.7% decrease over the annual. The forecasted values of malaria cases from the decomposition method are shown in Table 4 for January 2024 to December 2024.

Table 4: Decomposition Forecasts

Period	(Jan. 2024)	(Feb. 2024)	(Mar. 2024)	(Apr. 2024)	(May 2024)	(Jun. 2024)
Cases	99.024	129.785	215.196	365.617	402.129	431.158
Period	(Jul. 2024)	(Aug.2024)	(Sep. 2024)	(Oct. 2024)	(Nov.2024)	(Dec. 2024)
Cases	317.668	253.244	166.019	139.253	86.718	88.585

Holt-Winters' method of forecasting the monthly malaria fever cases

Applying the Holt-Winter's method to forecast monthly malaria fever cases, Table 5 shows selection results for the best Holt Winter's model that fits.

Table 5: Holt Winter's Selection Table for the best Fits

α	β	γ	MAPE	MAD	MSD
0.1	0.1	0.1	46.82	61.94	6544.96
0.1	0.2	0.2	470.40	65.22	7606.59
0.1	0.1	0.2	46.52	62.09	6535.14
0.2	0.1	0.1	44.86	61.34	7060.72
0.2	0.2	0.1	46.54	64.53	8253.49
0.2	0.1	0.2	44.63	61.78	7144.54
0.2	0.2	0.2	46.19	64.96	8288.75
0.3	0.2	0.1	44.84	63.46	8092.86
0.3	0.2	0.2	44.35	63.62	8391.51
0.3	0.3	0.2	45.66	66.49	9628.69
0.3	0.3	0.3	45.71	66.57	9931.07
0.3	0.1	0.1	43.48	60.39	7075.23
0.3	0.1	0.3	42.91	61.27	7417.77
0.9	**0.1**	**0.1**	**39.92**	**56.84**	**6151.10**

To obtain the best fitted model to the data, the weights of three smoothing parameters which are level (α), trend (β) and seasonal (γ) are varied, and their corresponding measures of accuracy are obtained. Table 5 gives the varied parameters values and their corresponding values of each measure of accuracy. The least values of the measures of accuracy, MAPE, MAD and MSD are 39.92, 56.84 and 6151.10 respectively, and the three parameters' values for the model are $\alpha = 0.9$, $\beta = 0.1$, and $\gamma = 0.1$. The fitted Holt-Winter's model to the data is when the weight of level is at 0.9, the weight of trend is at 0.1 and the weight of seasonal is at 0.1.

The monthly forecasted values for the year 2024, for malaria fever cases are presented below in Table 6.

Table 6: Holt Winter's Forecasts

Period	(Jan. 2024)	(Feb. 2024)	(Mar. 2024)	(Apr. 2024)	(May 2024)	(Jun. 2024)
Cases	56.226	66.445	100.396	156.254	186.500	176.839
Period	(Jul. 2024)	(Aug.2024)	(Sep. 2024)	(Oct. 2024)	(Nov.2024)	(Dec. 2024)
Cases	128.319	91.890	61.728	47.784	35.649	30.890

SARIMA method of forecasting monthly malaria fever cases

All possible SARIMA models were fitted to the monthly malaria fever cases, and the performance of the model is measured using Akaike Information Criterion (**AIC**). These results are shown in Table 7.

Table 7: AIC measures for selected SARIMA model for monthly malaria fever cases

SARIMA (p, d, q)×(P, D, Q)

Model	AIC
SARIMA (0,0,2) ×(1,1,2)	2075.15
SARIMA (0,0,2) × (0,1,2)	2071.23
SARIMA (0,0,2) × (1,1,1)	2069.19
SARIMA (0,0,2) × (2,1,2)	2067.16
SARIMA (0,0,2) × (0,1,1)	2065.23
SARIMA (0,0,2) × (2,1,1)	2061.17
SARIMA (0,0,1) × (1,1,2)	2052.27
SARIMA (1,0,2) × (1,1,2)	2052.21
SARIMA (0,0,3) × (1,1,2)	2052.18
SARIMA (0,0,1) ×(1,1,2)	**2051.15**

From Table 7, the SARIMA model with the lowest AIC value, which is 2051.15, is SARIMA (0,0,1) × (1,1,2) among the computed models. Hence it is the best fitted model for monthly malaria fever cases.

Table 8: Final Estimates of Parameters

Coefficient	Estimate	Std-Error	T-Value	P-Value
MA1	0.37	0.06	6.02	0.00
SAR1	0.04	0.75	0.05	0.96
SMA1	-0.81	0.75	-1.09	0.28
SMA2	0.09	0.55	0.15	0.88

In Table 8, the significant estimated parameter is Moving Average at lag 1 with a coefficient of 0.37, which means that as shock increases from 12 months ago, the malaria fever cases will increase by 0.37.

Table 9: Modified Box-pierce (Ljung Box) Chi-square statistic

Lag	12	24	36	48
Chi- square	20.273	32.663	40.89	61.378
DF	12	24	36	48
p-value	0.06209	0.1114	0.2644	0.09299

Table 9 shows the Ljung Box Chi-Square statistic with its p-value for lags 12, 24, 36, and 48. In the results, the p-value of the lags are all greater than 0.05, indicating no evidence of autocorrelation at those lags.

Table 10: SARIMA's Forecast with 95% Limits

Year	Month	Forecast	Lower	Upper
2024	Jan	71.53063	-63.934360	206.9956
2024	Feb	101.68538	-42.862891	246.2336
2024	Mar	196.01499	51.466720	340.5633
2024	Apr	310.83636	166.288093	455.3846
2024	May	333.55843	189.010160	478.1067
2024	Jun	316.86170	172.313435	461.4100
2024	Jul	199.64287	55.094597	344.1911
2024	Aug	188.61987	44.071601	333.1681
2024	Sep	109.87396	-34.674310	254.4222
2024	Oct	136.93748	-7.610786	281.4857
2024	Nov	121.91180	-22.636470	266.4601
2024	Dec	115.58854	-28.959710	260.1368

Table 10 shows the actual monthly malaria fever cases data and the forecasts from the SARIMA (0,0,1) × (1,1,2) method.

Comparing the forecasts of the three methods

Table 11 shows the actual monthly malaria fever cases and the forecasts from the Decomposition, Winters' and SARIMA methods.

Table 11: The actual Monthly Malaria Fever Cases and the forecasts from the Decomposition, Winters' and SARIMA methods.

Month in Year 2024	Actual Values	Forecast (Decomposition)	Forecast (Winter's)	Forecast (SARIMA)
January	105	99.024	56.226	71.5306
February	112	129.785	66.445	101.6854
March	167	215.196	100.396	196.0150
April	452	365.617	156.254	310.8364
May	312	402.129	186.500	333.5584
June	284	431.158	176.839	316.8617
July	130	317.668	128.319	199.6429
August	245	253.244	91.890	188.6199
September	211	166.019	61.728	109.8740
October	251	139.253	47.784	136.9375

Month in Year 2024	Actual Values	Forecast (Decomposition)	Forecast (Winter's)	Forecast (SARIMA)
November	134	86.718	35.649	121.9118
December	101	88.585	30.890	115.5885

Table 12 shows computed RMSE values of Decomposition, Winter's, and SARIMA methods for monthly malaria fever cases.

Table 12: RMSE of Malaria Fever Cases for Decomposition, Winter's, and SARIMA methods

Month	**Decomposition** $(y_t - \hat{y}_t)^2$	**Winters'** $(y_t - \hat{y}_t)^2$	**SARIMA** $(y_t - \hat{y}_t)^2$
January	35.713	2378.903	1120.199
February	316.306	2075.258	106.391
March	2322.854	4436.093	841.870
April	7462.023	87465.697	19927.173
May	8123.237	15750.250	464.766
June	21655.477	11483.480	1079.891
July	35219.278	2.826	4850.882
August	67.964	23442.672	3178.719
September	2023.290	22282.130	10226.476
October	12487.392	41296.743	13010.258
November	2235.588	9672.919	146.125
December	154.132	4915.412	212.825
Total	**92103.25**	**225202.4**	**55165.58**
RMSE	**87.6086**	**136.9922**	**67.8022**

The RMSE for Decomposition method is 87.6086. The RMSE for Winters' method is 136.9922. The RMSE for SARIMA method is 67.8022. The least RMSE value is from SARIMA method. SARIMA (0,0,1) × (1,1,2) is the best method in predicting monthly malaria fever cases.

CONCLUSION

In forecasting malaria fever cases, Holt-Winter's method with the weight of level at 0.9, the weight of trend at 0.1, and the weight of seasonal at 0.1, fits and predicts the data. Decomposition method fits and predicts the data better than Holt Winter's method. SARIMA method with the model SARIMA (0,0,1) × (1,1,2), best fits and predict the data than Decomposition method and Holt-Winter's method.

Based on the results from the study, it is recommended that prevention strategies should be in place to avert higher malaria cases experienced from April to August, period of high volume of rain, in the study area. Forecasting malaria fever cases, SARIMA method is recommended the most.

REFERENCES

Adenomon M. O. and Ojehomon V. E. T. (2014). A Comparison Of Decomposition Time Series Method And Winters' Seasonal Exponential Smoothing In Forecasting Seasonal Temperature In Niger State, Nigeria. International Journal of Mathematics and Statistics Research Vol.1, No.1, pp.10-16. Published by British Research Institute UK (www.gbjournals.org)

Adenomon M.O., Oyejola B. A. and Ojehomon V. E. T. (2014): Comparison of Decomposition Time Series Method and Winters' Seasonal exponential Smoothing in Forecasting Seasonal Temperature in Niger State, Nigeria. Journal of Nigerian Statistical Association. 26:20-34.

Anwar M.Y., Lewnard J.A., Parikh, S. and Pitzer V.E. (2016). Time series analysis of malaria in Afghanistan: using ARIMA models to predict future trends in incidence. *Malar J* **15**, 566 (2016). https://doi.org/10.1186/s12936-016-1602-1

Ashraf S., Ali N., Khan M.I., Niaz A. and Masood (2024). Weather Forecasting: Using Time Series Analysis Under Different Stations Of The UK. Migration Letters Volume: 21, No: S9 (2024), pp. 782-794.

Ayiah-Mensah, Bosson-Amedenu S., Addor J.A., and Baah E.M. (2025). Advancements in seasonal rainfall forecasting: A seasonal auto-regressive integrated moving average model with outlier adjustments for Ghana's Western Region Francis. Scienti African 28 (2025) e02632

Box G.E.P and Jenkins G.M. (1976). Time Series Analysis, Forecasting and Control: San Francisco. Holden Day. Pp. 89-96

Centre for Disease Control, Malaria. (2024). Malaria's Impacts Worldwide. Cdc.gov/malaria/php/impact/indexhtml. April 1st.

CP (2024) https://www.citypopulation.de/en/nigeria/admin/taraba/NGA035007__jalingo/

Cooray T.M.J.A. (2008). Applied Time Series Analysis and Forecasting. New Delhi: Narosa Publishing House

Das P. and Barman S. (2025). Predictive Chapter: An Overview of Time Series Decomposition and Its Applications. Doi:10.5772/intechopen.1009268. https://www.intechopen.com/online-first/1205228

Ferbar L. and Strmcnik E. (2016). The comparison of Holt–Winters Method and Multiple Regression Method: A case study. Proceedings of the ICE - Energy 109:266-276. DOI:10.1016/j.energy.2016.04.115

Kwarteng S.B. and Andreevich P.A. (2024). Comparative Analysis of ARIMA, SARIMA and Prophet Model in Forecasting. Research & Development, Vol. 5, No. 4, pp. 110-120 https://doi.org/10.11648/j.rd.20240504.13

Lee S. (2025a). Mastering Exponential Smoothing for Time Series Forecasting Models. https://www.numberanalytics.com/blog/mastering-exponential-smoothing-forecasting-models#:~:text=Triple%20Exponential%20Smoothing%20(Holt%2DWinters%20Method),level%20of%20the%20time%20series.

Lee S. (2025b). Effective Forecasting Tools: Holt Winters Method Explained. https://www.numberanalytics.com/blog/8-effective-forecasting-tools-holt-winters-method-explained

Majka M. (2024). Seasonal Time Series Analysis: Why SARIMA outshines ARIMA. https://www.researchgate.net/publication/384196885_Seasonal_Time_Series_Analysis_Why_SARIMA_Outshines_ARIMA/citation/download

Pollock, D. S. G.(1993): A Short Course of Time Series Analysis and Forecasting. Queen Mary and Westfield College, The University of London.

Robertson, J. C. and Tallman, E. W. (1999): Vector Autoregressions: Forecasting and Reality. Economic review (Atlanta Federal Reserve Bank). 84(1):4-18.

Rudasingwa G. and Cho S. (2024). Malaria Prevalence and Associated Population and Ecological Risk Factors among Women and Children Under 5 Years in Rwanda. Heliyon 10 (2024) e34574. www.cell.com/heliyon

Schantz-Dunn J. and Nour N.M. (2009). Malaria and Pregnancy: A Global Health Perspective. Rev Obstet Gynecol. Summer; 2(3):186–192.

Soni A. (2024). Predictive Time Series Modeling of Malaria Incidence in India: A 20-Year Retrospective and 5-Year Forecast. https://www.medrxiv.org/content/10.1101/2024.09.26.24314440v2.full.pdf

Thomas A., Bakai T.A., Atcha-Oubou T., Tchadjobo T., Bossard N., Rabilloud M., and Voirin N. (2021). Seasonality of Confirmed Malaria Cases from 2008 to 2017 in Togo: a Time Series Analysis by Health District and Target Group. BMC Infect Dis. 2021 Nov 26;21:1189. doi: 10.1186/s12879-021-06893-z

World Health Organisation, Malaria. (2024). https://www.who.int/news-room/fact-sheets/detail/malaria. December 11th.