Time series analysis of malaria fever prevalence in Ogun State

Adewole, A. I., Amurawaye F.F. & Oladipupo J.O
Department of Mathematics, Tai Solarin University of Education Ijagun Ogun State Nigeria.

ABSTRACT

Malaria fever remains the most important parasitic disease in terms of its public health implications. This research study investigated the trend and seasonality of malaria fever in Ogun State, Nigeria over the period 2016-2021 and also predict its prevalence in the year 2023. The study used secondary data obtained from the World Development Indicators. The data was pre-processed to ensure that it was in the appropriate format for time series analysis. The time series data was decomposed into its trend, seasonality, and residual components using the seasonal decomposition of time series (STL) method, ARIMA (Autoregressive Integrated Moving Average) modeling was used to describe the general behavior and pattern of occurrence of the malaria fever over the period under study and forecasts of future occurrence. It was revealed that relatively large number of infected patients during the study period are seasonal in nature. The results of this study predicted that there will be a 50% reduction in the trends of malaria fever in Ogun state for the year 2023 provided there are appropriate preventive and control measures in places. However, the study recommends that the Government and Malaria Control Agencies should provide more preventive measures and effective intervention strategies such as vaccines, mosquito nets, insecticides to control malaria fever in Ogun State.

Keywords: Times series analysis, Malaria fever, ARIMA Model and Model Decomposition

INTRODUCTION

World Health Organization (WHO, 2020) defines Malaria as an acute febrile illness caused by Plasmodium parasites. This plasmodium has four species which include plasmodium falciparum, plasmodium vivax, and plasmodium ovule and plasmodium malaria. Malaria parasite is transmitted from one person to another through the bite of an infected female Anopheles Mosquito which require blood to nurture her eggs. When Malaria parasites enter the blood stream of a person, they infect and destroy the red blood cells. The destruction of these essential cells leads to fever and flu-like symptoms such as chills, headache, muscle aches, tiredness, nausea, vomiting and diarrhea and when not treated, can lead to coma and hence death. In the 19th century, Africa was called the "heartland" of malaria due to the massive effect of malaria on the mortality rate of the Africans in the 90's (Robert, 2012). Malaria remained a threat to many citizens of Africa as there was a very minimal control measures to tackle the spread of malaria (WHO, 2017). A systematic analysis of recent literature on the prevalence of malaria in pregnancy from many authors was carried out and the facts synthesized to make an easy read. From the analysis of literature, Ten Thousand women and 200,000 babies were reported to be dying annually from complications of malaria in pregnancy which recorded a prevalence of 85 per cent in sub-Saharan Africa (Joseph *et al.*, 2020). Malaria is responsible for over 10% of the overall African disease burden. Children under five years of age (22% of the population) and pregnant women (20% of the population) are the most vulnerable to Malaria disease (Gillet *et al.*, 2010). Researchers ascertained in the medical reports that barely every two minutes, a child dies of malaria (Stefan Swartling Peterson, UNICEF Chief of Health). Worse yet, after years of progress the most recent year-on-year trend is pointing in the wrong direction. Renewed political commitment and funding is a must if we are going to beat malaria. Far too many children' s lives are at stake. A separate statement by Malaria Consortium echoed that two groups most at risk from malaria are pregnant women and children under five and that more needs to be done to prioritize support for these groups. It also called for increased commitment to put an end to the disease. The programs put in place to reduce transmission of malaria in Nigeria include mass distribution of insecticide-treated bed nets (ITNs) and intermittent preventive treatment (IPT) with sulfadoxine– pyrimethamine (SP) during pregnancy. There is an urgent need to increase access to and

use of IPTp for pregnant women in malaria-endemic countries if the world wants to come close to achieving the WHO's malaria targets over the next decade (Ayodamola, 2019). While the rapid scale-up of ITN distribution in Africa represents an enormous public health achievement, it also represents a formidable challenge for the future in ensuring that the high levels of coverage are maintained. Malaria mortality in Nigeria accounted for about 30% of the world total, and its associated burden relates to approximately 60% of outpatient visits to health facilities. It is therefore important to carry out this study in order to figure out some contributing factors that led to the increase or decrease of malaria occurrences and as well as mortality rate (Unicef, 2018). Several works have been done in modelling the prevalence of malaria trends in Nigeria and sub-Africa at large (Mohammad 2016, Adeboye 2018, Getahumu 2019, Okunola *et a*l 2021, among others). The Primary objective of this research study is to identify the trend of the prevalence of malaria fever in Ogun State and predict future occurrence using Box-Jenkins procedures. In particular, this study describes the appropriate model, its application and also estimate the parameters of the model. The study therefore attempts to consider Ogun State, Nigeria as a case study thereby bringing to limelight the diverse predictions of malaria fever occurrences as evidenced by the World Health Organization (WHO).

MATERIALS AND METHODS

This section outlines the methodology used in analyzing the total number of people treated for malaria fever in Ogun State, Nigeria. The methodology includes data collection, preprocessing, time series visualization, stationary testing, time series decomposition, modeling, model evaluation, and forecasting

Data Collection

The data for this study was collected from the malaria records of WDI (World Development Indicator). WDI is a world bank of database for different organizations and institutions. The data consists of the total number of people treated for malaria fever in Ogun State, Nigeria over the periods 2017-2022. The data was collected yearly and further decomposed into monthly.

Data Preprocessing

Before analyzing the data, it is necessary to pre-process the data to ensure that it was in the appropriate format for time series analysis. The preprocessing steps included:

Checking for missing values and replacing or imputing any missing values as necessary

Checking for outliers and transforming the data if necessary to remove outliers

Checking for seasonality and taking the first differences of the data if necessary to make it stationary.

Stationarity Testing

The stationarity of the time series data was tested using the Augmented Dickey-Fuller (ADF) test. The ADF test was used to test the null hypothesis that the time series data is non-stationary. The ADF test compares the ADF statistic to critical values from a standard normal distribution to determine whether to reject or fail to reject the null hypothesis If the series is not stationary; it would then be converted to a stationary series by differencing before it can be modeled. The Phillips-Perron test was used to addresses some of the limitations of the Dickey-Fuller test, such as the assumption of normally distributed errors and the presence of serial correlation in the data, The test statistic is based on the augmented Dickey-Fuller (ADF) test and testing the null hypothesis of the presence of a unit root in the residuals, the critical values were adjusted for serial correlation and heteroskedasticity in the data.

Modeling of Vector Auto Regressive Model

The general form of a VAR model with p lags is given by:

$$Y_t = A_1 Y_{\{t-1\}} + A_2 Y_{\{t-2\}} + \cdots + A_p Y_{\{t-p\}} + E_t \quad (1)$$

Where Y_t is a k-dimensional vector of variables at time t is, A_i are $k \times k$ matrices of coefficients for the i-th lag, E_t is a k-dimensional vector of error terms at time t, and p is the number of lags.

To estimate the parameters of the VAR model, maximum likelihood estimation was used to estimate the coefficients A_i and the error covariance matrix Σ.

Time Series Decomposition

The time series data was decomposed into its trend, seasonality, and residual components using the seasonal decomposition of time series (STL) method. The STL method is a robust method for time series decomposition that is well-suited for data with strong seasonality. The decomposition of the time series data was visualized using a plot of the trend, seasonality, and residual component

Time Series Modeling

The time series data was modeled using the Autoregressive Integrated Moving Average (ARIMA) model. The parameters for the ARIMA model will be chosen using the Box-Jenkins method, which is a systematic method for identifying the optimal parameters for an ARIMA model**.** Box-Jenkins forecasting models consist of a four-step iterative procedure as follows; Model Identification, Model Estimation, Model Checking (Goodness of fit) and Model Forecasting. The four iterative steps are not straight forward but are embodied in a continuous flow chart depending on the set of data understudy

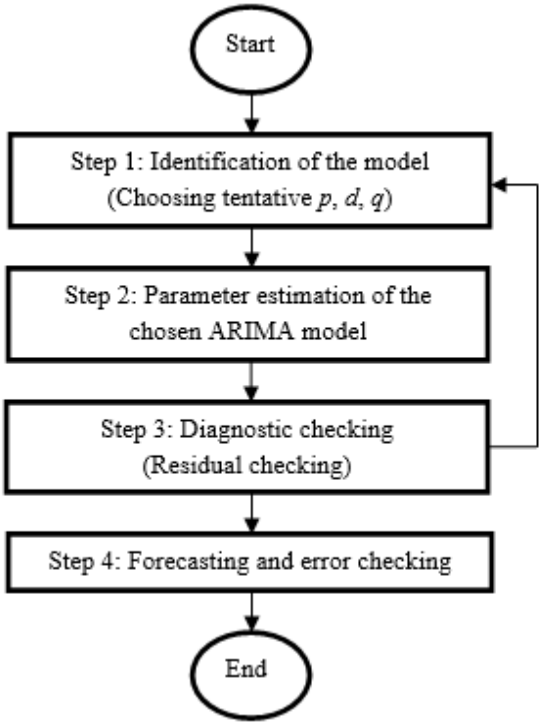

Fig. 1: Statistical forecasting procedure

The main part of the ARIMA model combines *AR* and *MA* polynomials into a complex polynomial, as seen in (1) below. The ARIMA (*p, d, q*) model is applied to all the data points of the data involved

$$X_t = \mu + \sum_{i=1}^{p} (\sigma x_{t-1}) + \sum_{i=1}^{q} (\theta \varepsilon_{t-1}) + \varepsilon_t \quad (2)$$

where the notation is as follows:

μ: the mean value of the time series data;
p: the number of autoregressive lags;
σ: autoregressive coefficients (*AR*);
q: the number of lags of the moving average process;
Θ: moving average coefficients (*MA*);
$\mathcal{E}$: the white noise of the time series data;
d: the number of differences calculated from
$\Delta y_t = y_t - y_{t-1}$
(3)

Model Evaluation

The performance of the ARIMA model was evaluated using several metrics such as Akaike Information Criteria, Bayesian Information Criteria. Model diagnostic checking is accomplished, in this work, through careful analysis of the residual series, sample correlation and a diagnosis test. Ljung-Box Q statistic

The test statistic Q is given as

$$Q_m = n(n=2) \sum_{k-1}^{m} \frac{\hat{r}_k^{\,2}}{n-k} \sim \chi^2_{m-r} \quad (4)$$

where $\hat{r}_k^{\,2}$ is the estimated autocorrelation of the series at lag k, and m is the number of lags being tested, n is the number of residuals, and m is the number of times lags is included in the test.

Predictions

Finally, the ARIMA model will be used to make predictions for the total number of people treated for malaria fever in Ogun State in the future. The predictions will be made for a specified number of future months and will be compared to actual values to assess the accuracy of the model.

RESULTS AND DISCUSSIONS

Table 1: Monthly Descriptive Statistics of Malaria Cases among Children, Adults and Pregnant Women for the period 2016-2021

Months	Children		Adult		Pregnant Woman	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
January	18.2000	9.13844	35.5000	16.55462	9.0000	5.53775
February	21.9000	6.34998	38.7000	5.65784	6.9000	3.47851
March	21.7000	9.69593	36.5000	14.94620	7.4000	5.14674
April	36.2000	10.00888	55.3000	18.60735	13.1000	6.95142
May	39.8000	14.53578	68.7000	17.94467	17.7000	12.21156
June	69.0000	16.84571	121.4000	33.78099	38.4000	19.19606
July	109.5000	42.68294	188.6000	57.38021	54.5000	18.17355
August	1110.1000	35.49789	184.6000	39.85864	43.8000	18.70710
September	103.3000	37.17541	169.1000	42.89121	55.8000	22.64116
October	69.9000	16.07932	113.1000	18.70502	35.0000	16.32993
November	54.4000	19.40332	110.4000	34.45190	30.2000	23.53626
December	39.1000	9.32678	60.7000	16.07655	12.8000	2.78089

Table 1 shows the monthly descriptive statistics of number of malaria cases among children, adults and pregnant women. The datasets indicated that malaria cases increase from the months of April to August and gradually reduced from September to December.

Table 2: Stationarity check of the data

	ADF Test		P-P Test		
Series	**Test Statistic**	**P-Value**	**Test Statistic**	**P-Value**	**Remark**
Children	-4.715	0.0001	-4.496	0.0002	Stationary at level
Adult	-3.866	0.0023	-3.422	0.0001	Stationary at level
Pregnant Women	-5.779	0.0000	-5.818	0.0000	Stationary at level

Table 2 shows the stationary test using Augmented Dickey-Fuller Test and Phillips-Peron Unit Root test, from Table 2, the p-value for the Augmented Dickey-Fuller (ADF) and Phillips-Perron (P-P) tests are all less than the 0.05 significance level. Therefore, we do not accept the null hypothesis and conclude that there is an indication of stationarity, which shows that the dataset for malaria cases among children, adult and pregnant women are stationary

Table 3: Jarque-Bera (J-B) Test

Series	J.B	p-value	Skewness	p-value	Kurtosis	p-value
Children	40.987	0.00000	12.903	0.0003	28.084	0.00000
Adult	23.898	0.00001	4.930	0.0263	18.968	0.00001
Preg. women	13.720	0.00099	9.028	0.0026	4.807	0.02834

The result for Jarque-Bera, Skewness and Kurtosis tests of residuals normality presented in Table 3 shows that the residual are not normally distributed. Since the p-values are all less than the 5% level of significant, there is no enough evidence to reject the null hypothesis of residuals normality. Therefore, variables are jointly not normally distributed

Table 4: Lag selection

Lag	LLL	LR	Df	P	FPE	AIC
0	-1508.28				2.9e+08	27.9867
1	-1447.43	121.71	9	0.000	1.1e+08	27.0264
2	-1441.52	11.806	9	0.224	1.2e+08	27.0838
3	-1425.07	32.907	9	0.000	1.0e+08*	26.9458*
4	-1421.76	6.6312	9	0.675	1.1e+08	27.0510
5	-1414.28	14.945	9	0.092	1.2e+08	27.0793
6	-1411.86	4.8445	9	0.848	1.3e+08	27.2011
7	-1408.45	6.8155	9	0.656	1.5e+08	27.3047
8	-1398.58	19.745	9	0.020	1.5e+08	27.2885
9	-1391.41	14.333	9	0.111	1.5e+08	27.3225
10	-1387.13	8.557	9	0.479	1.7e+08	27.4099
11	-1382.81	8.6472	9	0.470	1.9e+08	27.4965
12	-1367.96	29.711*	9	0.000	1.7e+08	27.3881

Table 4 suggested lag three (3) as the optimal lag for VAR model which contains malaria cases among children, adult and pregnant women level. At lag three (3) the test has relatively small value of AIC (26.9458). The results of modeling the VAR for malaria cases are presented in Table 4. The P-values indicate that only the lag one values of the adult variable are statistically significant in the children equation at the 5% level. The adult at lagged one, the pregnant women at lagged three are statistically significant in the adult equation. The adult at lagged one, pregnant women at lagged two and three are significant in the pregnant women equation.

Table 5: Modeling of Vector Auto Regressive Model

	Coef.	Std. Err	Z	P- value	95% Conf.	Interval
Children						
L1	.0792779	.122856	-0.67	0.505	-.3226313	.1589553
L2	.1469114	.1249242	0.63	0.526	-.1655691	.3241249
L3	-.081838	.1165946	1.26	0.208	-.0816098	.3754326
Adult						
L1	.4653475	.0773021	6.02	**0.000***	.3138381	.6168568
L2	.0339745	.087957	0.39	0.699	-.1384181	.2063672
L3	.0336252	.0867141	0.39	0.698	-.1363314	.2035818
Pregnant						
L1	-.0053751	.1675313	-0.03	0.974	-.3337305	.3229803
L2	-.2454616	.1669133	-1.47	0.141	-.5726056	.0816824
L3	-.008135	.1691717	-.0.05	0.962	-.3397055	.3234356
_cons	3.845261	4.262685	O.90	0.367	-4.509448	12.19997
Adult						
Children						
L1	.2337037	.1857665	1.26	0.208	-.1303919	.5977993
L2	.2459947	.1888938	1.30	0.193	-.1242304	.6162197
L3	.1257458	.1762988	0.71	0.476	-.2197935	.471285
Adult						
L1	.4325729	.116886	3.70	0.000	.2034806	.6616651
L2	.516103	.1329969	0.39	0.698	-.2090589	.3122794
L3	-.0441962	.1311176	-0.34	0.736	-.3011819	.21277895
Pregnant women						

L1	-.0558098	.2533186	-0.22	0.826	-.5523051	.4406855
L2	-.4586229	.252384	-1.82	0.069	-.9532865	.0360407
L3	.819874	.255799	3.21	**0.001***	.3185172	1.321231
_cons	12.35782	6.445465	1.92	0.055	-.2750636	24.99069
Pregnant women						
Children						
L1	.0676454	.0799261	0.85	0.397	-.0890068	.2232976
L2	.1295535	.0812716	1.59	0.111	-.0297359	.2888429
L3	.1236901	.0758526	1.63	0.103	-.0249782	.2723585
Adult						
L1	.1855702	.0502906	3.69	**0.000***	.0870032	.2841372
L2	-.0183594	.0572219	-O.32	0.748	-.1305124	.0937935
L3	-.0678943	.0564134	-1.20	0.229	-.1784624	.0426739
pregnant women						
L1	-.0589954	.1089904	-0.54	0.588	-.2726126	.1546217
L2	-.2285306	.1085883	-2.10	0.035	-.4418597	-.0157014
L3	.26668	.1100576	2.42	**0.015***	.0509711	.4823888
_cons	-.708047	2.773162	-0.26	0.798	-6.143345	4.727251

It can be observed from Table 5 that, the children equation, for adult at lagged one is significantly affected positively with malaria by 46% for a unit change in its lagged values. From adult equation, it can be observed that children are affected positively with malaria by 23% for a unit change in its lagged values. From pregnant equation, it can be observed that children are affected positively with malaria by 6% and adult affected positively with malaria by 19% for a unit change in its lag

Table 6: **Results of Lagrange-Multiplier (LM) Test**

Lag	χ^2	**Df**	**P-value**
1	6.1897	9	0.72080
2	15.4609	9	0.07903
3	5.9493	9	0.74498
4	4.4549	9	0.87901
5	10.3999	9	0.31909
6	5.2071	9	0.81590
7	10.7439	9	0.29317
8	10.4876	9	0.31247
9	16.2176	9	0.06247

***H*o: No autocorrelation at lag order**

Table 6 gives the results for the Breusch-Godfrey Lagrange multiplier (LM**)** test for the residual serial correlation of VAR (3) model. It can be seen from Table 6 that the P-values are greater than 0.05. The LM test in Table 6 suggests no autocorrelation at each lag. Besides, residuals are randomly distributed. Therefore, residuals in VAR model have no autocorrelation problem since the associated p-value is greater than the 0.05 significance lev

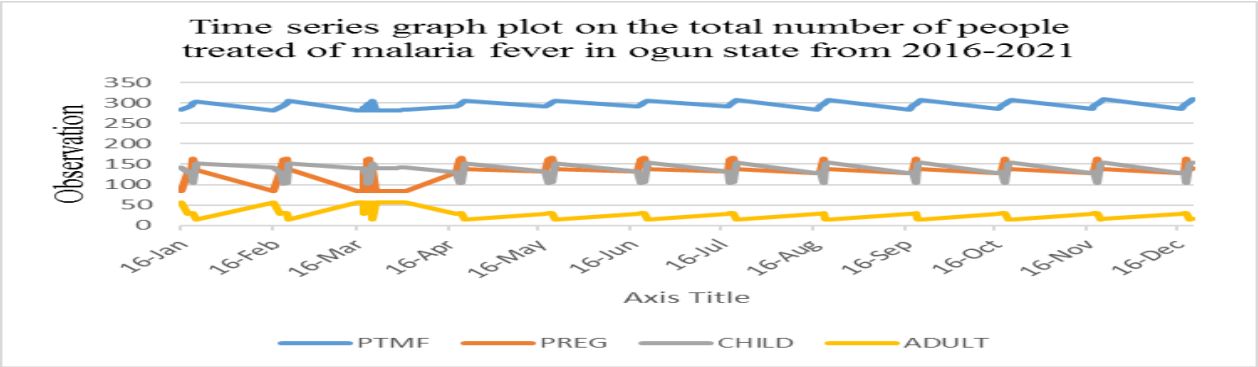

Figure 2: Time series graph plot on the total number of people treated of malaria fever in Ogun state from 2016-2021

Figure 2 is the graphical illustration and analysis of average monthly data obtained from World Development Indicators from January, 2016 to December, 2021. From the graphical representation in figure 2 above it appeared that the number of children, adults, and pregnant women who were affected by malaria fever was increasing gradually from January, 2016 to December, 2021.The findings from the study provided information on the seasonality and trends of malaria fever in Ogun State thereby helping us to identify that there was a high rate in the infection over the years 2016-2021. This could be as a result of a low turnout in managing and controlling the burden of malaria fever in Ogun state by the government and malaria agencies. The analysis of the data revealed that malaria occurred mostly amongst children and pregnant woman than the adults. The analysis of the data also revealed that there were no observable seasonal fluctuations in the trend of occurrences of Malaria Fever over the years 2016-2021 in Ogun state as there are no noticeable irregularities which could have been caused by different factors such as rainfall, war, winter, humidity and so on. The infection keeps increasing over the years. This research study has been able to help us understand that there is every tendency for the outbreak of malaria fever to keep increasing if there are no preventive and control measures to bring about reduction in the trends of malaria fever in Ogun state.

Table 7: ARIMA RESULT

Model	**Specification (*p, d, q*)**	**AIC**	**AICc**	**BIC**
Model 1	ARIMA (0,1,1)	198.42	196.75	190.18
Model 2	ARIMA (0,1,2)	187.99	188.65	193.05
Model 3	ARIMA (1,1,1)	198.83	189.49	183.89
Model4	ARIMA (1,1,2)	**170.82**	**171.96**	**182.57**
Model5	ARIMA (2,1,2)	182.69	184.45	191.13

The values in bold fonts are the least for each category. The ARIMA (1,1,2) was chosen as the best model.

Table 8: Model Parameters for the most preferred Model

	Estimate	
Component	**Coefficient**	**Standard Error**
AR (1)	0.1452	0.0219
MA (2)	-0.3478	0.1517

Table 8 gives the estimated model parameters. The parameters were estimated using the log likelihood. Along with the model parameters were the standard error of each of the estimated parameters. If the model has been correctly identified, the highest order *AR* or *MA* coefficient should be significantly different from zero according to the usual standard for a regression model, that is, it should have a significant *t*- statistic. The fitted models are given below;

$$y_t = 0.1452y_{t-1} - 0.3478\epsilon_{t-1} + \epsilon_t \quad (5)$$

based on the highest order coefficients (AR1 and MA2)

Model Diagnostics and Potential Improvement

After the selection of the most preferred model, the next step is the diagnosis of the selected model. ACFs and PACFs for the residuals of the model are examined. As recommended by Pankrantz (1983), if the residuals represent only a random error, the absolute value of *t* for autocorrelation at each of the first three lags should be less than 1.25 and for later lags, less than 1.60. However, as McCain and McCleary (1979) point out, if there are many lags (say 30 or more), one or two of the higher-order lags may exceed this criterion by chance if the residuals are essentially random. This is easier detected on the ACF and PACF plots. The rule for analyzing the residual ACF and PACF plots is given below;

i. Spikes in the residual ACF plot at lags 1, 2, or 3 signify a need for a higher value of *q*
ii. Spikes in the residual PACF plot at lags 1, 2, or 3 indicate a need for a higher order of *p*

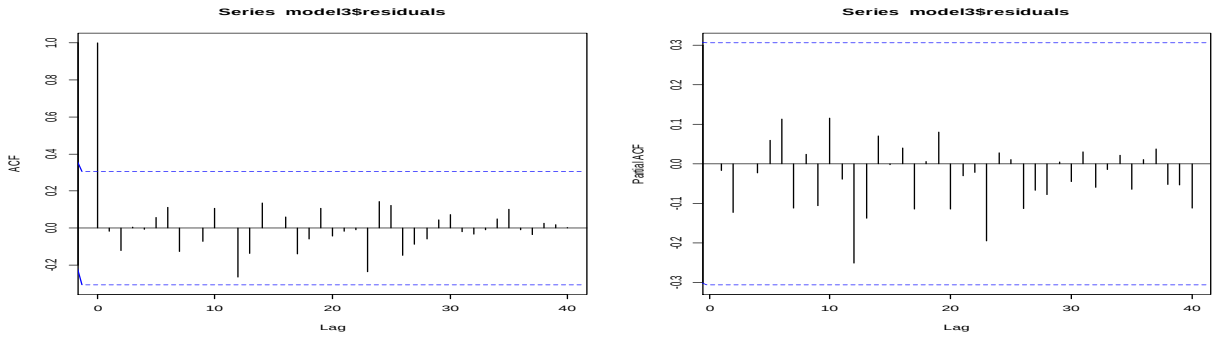

Figure 3: ACF and PACF plots of residuals

Figure 3 gives the ACF and PACF plot of the residuals and with careful observation. None of the residuals are significant (none of the value went outside the confidence range (the blue lines)) for both the ACF and PACF plot. To affirm the claim, Ljung Box test was used to test the absence of serial autocorrelation, up to a specified lag *k*. The *p*-vales for the Ljung-Box statistic exceed the threshold (5%), implying that there is no significant departure from white noise for the residuals.

Table 9: Monthly Forecast of Malaria Cases among Children, Adult and Pregnant Women for the Year 2023

Year	Month	Children	Adult	Pregnant women
2023	January	33	64	15
2023	February	41	66	17
2023	March	39	66	18
2023	April	39	68	17
2023	May	41	71	19
2023	June	43	74	19
2023	July	44	74	19
2023	August	44	76	20
2023	September	45	78	21
2023	October	46	79	21
2023	November	47	81	21
2023	December	48	82	22

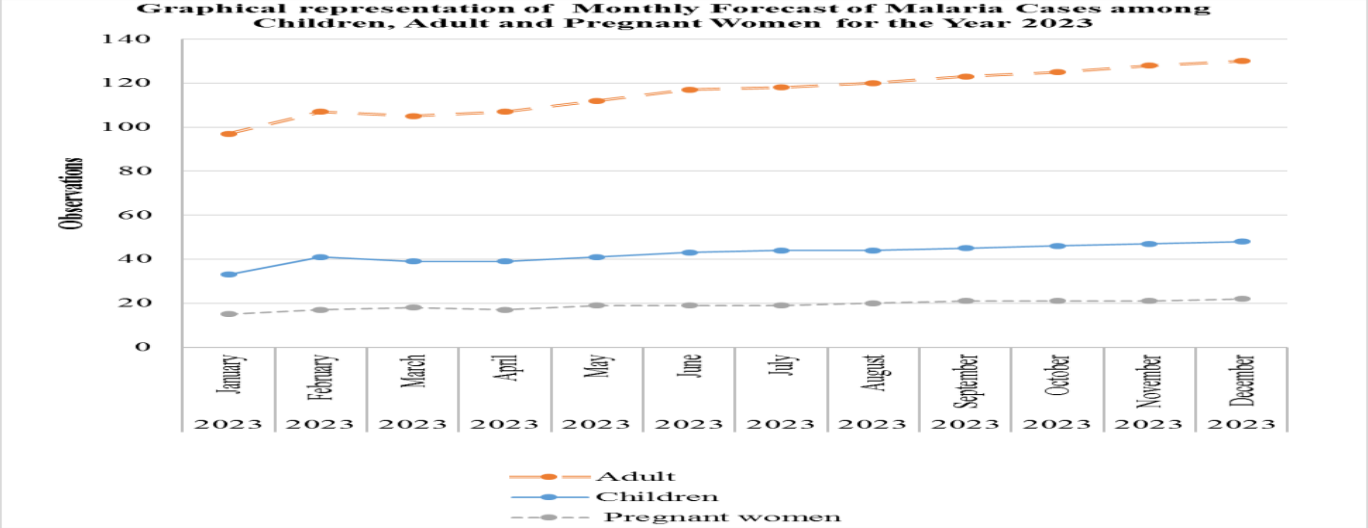

Figure 4: Time Series graph plot of Monthly Forecast of Malaria Cases among Children, Adult and Pregnant Women for the Year 2023

In comparison with the obtained data, the forecasted malaria predictions show in the figure 4 above that, provided there are more preventive measures and effective intervention strategies to control malaria fever in Ogun State, the trend of malaria fever will be reduced by 50% in the year 2023

CONCLUSION

In this research, malaria cases among children, adult and pregnant women using multivariate time series (VAR) model were modelled. Prediction was made for the future prevalence of malaria trends in Ogun state in Nigeria using ARIMA. The time series data showed an upward trend, five different ARIMA models were fitted to the time series data and the best was selected using model performance criteria. The best model did not show lack of fit for the time series data, the overall fit of the model was ascertain using the Ljung Box test. The forecasted value shows that rates of malaria cases will be higher among adults, followed by children, and pregnant women every month. Generally, the rate will vary from month to month as cases may likely increases every month from January to December, 2023

To prevent or control the spread of malaria, it is important to implement measures such as mosquito control, use of insecticide-treated bed nets, early diagnosis, and treatment. Health education programs could also be implemented to raise awareness about the causes, symptoms, and prevention of malaria.

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