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MULTIVARIATE TIME SERIES ANALYSIS IN MODELLING MALARIA CASES IN JIMETA METROPOLIS OF ADAMAWA STATE, NIGERIA

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ABSTRACT

Sub-Sahara Africa harbours most of the Malaria burden including Nigeria. There are scanty studies that aim at modelling these cases particularly in the study area. This study therefore, focused on a multivariate time series model for malaria cases among the residents in Jimeta metropolis of Adamawa State. A secondary data on reported malaria cases for adults, pregnant women and children was collected from January 2011 to December 2020 on monthly basis from medical records at the specialist Hospital, Jimeta, Yola, Adamawa State. The vector autoregressive (VAR) model was employed for modelling. A descriptive analysis was performed on the data. The lag order selection for stationary VAR model suggest lag three as the optimal lag for VAR model with malaria cases among children, adult and pregnant women. To assess how well the model fit the data set, AIC of 26.9458 for model with lag (3) was best. The Breusch-Godfrey LM test for residual serial correlation of VAR model suggest no autocorrelation at each lag, there is no problem of autocorrelation, since the associated p-value is greater than the conventional 0.05 level of significance. Jarque-Bera test shows that the residuals are not normally distributed and the forecast made showed that, rates of malaria cases are higher among adult followed by children and then pregnant women.

Keywords: Malaria, Multivariate, Time Series, VAR

INTRODUCTION

Malaria continues to be an economic burden and a great threat globally and almost impossible to eradicate for the past six decades. Since the year 2000, progress in malaria control has resulted primarily from expanded access to in Sub-Sahara Africa and more especially Nigeria with vector control interventions, particularly about 25%. However, these gains are threatened by emerging resistance to insecticides among anopheles mosquitoes.

There are fewer or scanty research on application of statistical models in malaria cases for in Nigeria. Abeku *et al*., (2002) observed that the statistically advanced ARIMA models produced very good fit to the data. Laari (2011) in his research titled" Spatial analysis of malaria epidemiology in the Amanse west District Ghana" used Bayesian geostatitical approach to correlate relationship between the elevation and malaria risk using vector autoregressive models and vector error correction models. Zhou *et al* (2013) fitted a vector error correction model on mortality cases of two populations. Kuhe *et al.* (2015) studied the transmission dynamics of malaria incidence in Nigeria using Autoregressive Integrated Moving Average model to forecast the incidence of malaria infection in Nigeria.

Sarki *et al.* (2019) studied malaria infection in pregnant women attending primary health care centres in Gombe metropolis. Statistical Package for Social Science (SPSS) version 23 and Chi-square test was applied to determine the relationship between the variables. Li and Hardy (2011) considered four possible ways to generalize a single-population mortality model to one that fits two or more populations. Cairns *et al*. (2011) introduced a general framework for producing consistent mortality forecasts for a pair of related populations.

Dowd *et al.* (2011) designed a gravity mortality model for two related but different sized populations. A similar model has also been proposed by Jarner and Kryger (2011). Zhou *et al*. (2011) introduced a two-population mortality model with transitory jump effects, and applied it to pricing catastrophic mortality securitizations. Adegboye *et al.* (2016) used Spatial scan statistics to detect and test hotspots of malaria and cutaneous leishmaniasis (CL) in Afghanistan. Multivariate negative binomial model was used to determine the effects of environmental variables on malaria and CL which show an association between the incidence of malaria and CL in the studied areas.

Hussien and Yong (2018) offered a malaria prediction model by the use of Box-Jenkins statistics and historic malaria morbidity records for malaria-endemic areas in Kass zone, South Darfur, Sudan. Anwar *et al.* (2016) ARIMA models was used to forecast malaria incidence in Afghanistan in order to build a predictive tool for malaria surveillance.

Literature reviewed shows several statistical methods applied on malaria cases. Most of the reviewed literature tend to focus on the prevalence rate of malaria and their parasites using blood samples (Bassey and Nwakaku, 2017; Hamza *et al.*, 2014; Owoeye *et al.*, 2016; Adebajo *et al.*, 2014). Few studies carried out in Nigeria such as that of Adenomon and Evans (2014) in Niger State used Poisson regression and Negative binomial regression models to study the trend of malaria prevalence in Minna, using monthly malaria outpatient data. However, only malaria status was modelled and considered. Similar investigation was carried out in Nigeria by Iribhogbe and Odoya (2020) where chi-square test was employed to determine association between independent categorical variables and dependent variable. This paper applied multivariate time series analysis in modelling malaria cases in Jimeta metropolis of Adamawa State, Nigeria.

MATERIALS AND METHODS

Source of Data

A secondary data was collected from Medical Record Department of Specialists Hospital, Yola, Adamawa State. The data was on reported Malaria cases over the following groups of residents in Jimeta metropolis of Adamawa State: Adults, pregnant women and paediatric (children). Data was collected for the period of 10 years on monthly basis

beginning from January 2011 to December 2020. In this study the data collected were modelled using VAR models.

Methods of Data Analysis

Multivariate time series model was used to model malaria cases for the three groups earlier identified. Descriptive statistics such as mean and plots was used so as to identify the pattern of malaria disease infection among the targeted population in the study area. STATA Version 15 was used for analysing the data.

Ethical Clearance: Ethical clearance for this research was obtained from Ministry of Health, Adamawa state, Nigeria with reference number: ADHREC 24/06/2021/056

Model Specification: VAR Model

VAR model is useful for describing the dynamic behaviour of epidemiologic, health, economic and financial time series data for forecasting (Sims, 1980).

Let $Y_t = (y_{1t}, y_{2\,t} \ldots, y_{n\,t})'$ denote an *(n×1)* vector of variables. The VAR (p) model has the basic form (Hamilton, 1994):

$$Y_t = \boldsymbol{C} + \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \cdots + \prod_p Y_{t-p} + \varepsilon_t \quad (1)$$

where C is an *(n×1)* vector of constants and $\prod_j$ is an *(n×n)* matrix of coefficients for j = 1, 2, . . . , *p*. The *(n×1)*vector ε_t is a vector of white noise,

where

$$\mathrm{E}(\varepsilon_t) = 0 \text{ and } \mathrm{E}(\varepsilon_t \varepsilon_t') = \begin{cases} \Sigma, \text{ if } t = s \\ 0, \text{otherwise} \end{cases} \quad (2)$$

with Σ an *(n×n)* symmetric positive definite matrix.

In lag operator notation, the VAR(p) equation (1) is written as

$$\prod(\mathrm{L})\, Y_t = \mathrm{C} + \varepsilon_t \quad (3)$$

$$\prod(\mathrm{L}) = \mathrm{I}_n - \prod_1 L^1 - \prod_2 L^2 - \ldots - \prod_p L^p$$

The VAR(p) is stable if the roots of

$$\det(\mathrm{I}_n - \prod_1 Z - \prod_2 Z^2 \ldots - \prod_p Z^p) = 0 \quad (4)$$

lie outside the complex unit circle (have modulus greater than one), or, equivalently, if the Eigen values of the companion matrix

$$\mathrm{F} = \begin{pmatrix} \prod_1 & \prod_1 & \cdots & \prod_n \\ \mathrm{I}_n & 0 & \ldots & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \mathrm{I}_n & 0 \end{pmatrix} \quad (5)$$

have modulus less than one. A stable VAR(p) process is stationary and ergodic with time invariant means, variances, and autocovariances.

If Y_t is covariance stationary, then the unconditional mean is given by

$$\mu = (\mathrm{I}_n - \prod_1 \mathrm{L} - \ldots - \prod_p L_p)^{-1}\mathrm{C}$$

The mean-adjusted form of the VAR(p) is then

$$Y_t - \mu = \prod_1 (Y_{t-1} - \mu) + \prod_2 (Y_{t-2} - \mu) + \cdots + \prod_p (Y_{t-p} - \mu) + \varepsilon_t \quad (6)$$

The basic VAR(p) model may be too restrictive to represent sufficiently the main characteristics of the data. The general form of the VAR(p) model with deterministic terms and exogenous variables is given by

$$Y_t = \boldsymbol{C} + \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \cdots + \prod_p Y_{t-p} + \Phi \mathrm{D}_t + GX_t + \varepsilon_t$$

where D_t is an (*l*×1) matrix, X_t is an *(n×1)* vector, and Φ and G are parameter matrices, ($\mathrm{E}[X_t \varepsilon_t] = 0$).

Basic Form of the VAR Model (VAR (3))

$$\left.\begin{aligned} Y_{1t} &= B_{01} + B_{11}Y_{1t-1} + B_{12}Y_{2t-1} + B_{13}Y_{3t-1} + B_{14}Y_{1t-2} + B_{15}Y_{2t-2} + \\ &\quad B_{16}Y_{3t-2} + B_{17}Y_{1t-3} + B_{18}Y_{2t-3} + B_{19}Y_{3t-3} \\ Y_{2t} &= B_{02} + B_{21}Y_{1t-1} + B_{22}Y_{2t-1} + B_{23}Y_{3t-1} + B_{24}Y_{1t-2} + B_{25}Y_{2t-2} \\ &\quad + B_{26}Y_{3t-2} + B_{27}Y_{1t-3} + B_{28}Y_{2t-3} + B_{29}Y_{3t-3} \\ Y_{3t} &= B_{03} + B_{31}Y_{1t-1} + B_{32}Y_{2t-1} + B_{33}Y_{3t-1} + B_{34}Y_{1t-2} + B_{35}Y_{2t-2} \\ &\quad + B_{36}Y_{3t-2} + B_{37}Y_{1t-3} + B_{38}Y_{2t-3} + B_{39}Y_{3t-3} \end{aligned}\right\} \quad (7)$$

Where Y_{1t} = Adults, Y_{2t} = Pregnant women and Y_{3t} = Paediatric (children).

Augmented Dickey-Fuller (ADF) Test

Consider a simple AR (1) process:

$$Y_t = \boldsymbol{\rho} \mathrm{Y}_{t-1} + X'_t\, \boldsymbol{\delta} + \varepsilon_t \quad (8)$$

The ADF test was used to test the H_0 that a unit root is present in the series. Thus

$$\boldsymbol{\Delta} Y_t = \boldsymbol{\alpha} \mathrm{Y}_{t-1} + X'_t\, \boldsymbol{\delta} + \varepsilon_t \quad (9)$$

where $\boldsymbol{\alpha} = \boldsymbol{\rho}$-1 and $\boldsymbol{\Delta} Y_t = Y_t - Y_{t-1}$.

H_0: $\boldsymbol{\alpha}$=0

H_a: $\boldsymbol{\alpha}$<0 (10)

Therefore,

$$\boldsymbol{t_{cal}} = \frac{\hat{\boldsymbol{\alpha}}}{se(\hat{\boldsymbol{\alpha}})} \quad (11)$$

where $\hat{\boldsymbol{\alpha}}$ is the estimate of $\boldsymbol{\alpha}$, and $se(\hat{\boldsymbol{\alpha}})$ is the coefficient standard error.

The ADF test for an AR (p) process is given by

$$\boldsymbol{\Delta}\, Y_t = \boldsymbol{\alpha\rho}\, \mathrm{Y}_{t-1} + X'_t\, \boldsymbol{\delta} + \prod_1 \boldsymbol{\Delta} Y_{t-1} + \prod_2 \boldsymbol{\Delta} Y_{t-2} + \cdots + \prod_p \boldsymbol{\Delta} Y_{t-p} + U_t \quad (12)$$

The Akaike information criteria (AIC) was employed to test how well the model fits the data set.

$$AIC(p) = ln|\hat{\Sigma}(p)| + \frac{2}{T} pn^2 \quad (13)$$

Test of residual autocorrelation

The Portmanteau autocorrelation were employed. It tests that auto-covariances are zero, i.e.,

$$\mathrm{H}_0\text{: } \mathrm{E}(\varepsilon_t\, \varepsilon_{t-i}) = 0 \quad (\mathrm{i}=1,2,\ldots) \quad (14)$$

This is tested against the alternative that at least one auto covariance and hence, one autocorrelation is nonzero. The test statistics is based on the residual auto covariances and has the form

$$\mathrm{Q_h} = \mathrm{T}\sum_{j=1}^{h} tr(\hat{\boldsymbol{\gamma}}_j'\, \hat{\boldsymbol{\gamma}}_0^{-1} \hat{\boldsymbol{\gamma}}_j\, \hat{\boldsymbol{\gamma}}_0^{-1}) \quad (15)$$

where

$$\hat{\boldsymbol{\gamma}}_j = T^{-1} \sum_{t=j+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j} \quad (16)$$

and the $\hat{\varepsilon}_t$'s are the estimated residuals. For unrestricted residuals stationary VAR(p) process the null distribution of $\mathrm{Q_h}$ and approximated by $\chi^2(\mathrm{K}^2(\mathrm{h-p}))$ distributed if T and h approaches infinity such that $\mathrm{h/T} \rightarrow 0$

Aliter

$$\mathrm{Q_h}^* = T^2 \sum_{j=1}^{h} \frac{1}{T-j} tr(\hat{\boldsymbol{\gamma}}_j'\ \ \boldsymbol{\gamma}_0^{-1} \hat{\boldsymbol{\gamma}}_j \boldsymbol{\gamma}_0^{-1}) \quad (17)$$

instead of the original version (19).

Jarque-Bera Test (Normality of the Residuals)

The hypothesis is as presented below

$$\mathrm{H}_0\text{: } \mathrm{E}(u_t^s)^3 = 0 \text{ (skewness) and } \mathrm{E}(u_t^s)^4 = 3\text{(Kurtosis)} \quad (18)$$

H_a: $E(u_t^s)^3 \neq 0$ or $E(u_t^s)^4 \neq 3$(Kurtosis) (19)

Formulation of the Jarque-Bera test uses a mean adjusted form of the VAR (p) model

$\hat{u}_t = (y_t - \bar{y}) - \hat{A}_1 (y_{t-1} - \bar{y}) - \ldots - \hat{A}_p (y_{t-P} - \bar{y})$ (20)

$\hat{\Sigma}_u = \frac{1}{T-KP-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t^T$

let $\hat{p}$ be the matrix satisfying $\hat{p}\,\hat{p}^T = \hat{\Sigma}_u$ such that plim($\hat{p} - p$)=0

Now we define the standardized residuals and their sample moments

$$\hat{w}_t = \hat{p}^{-1}\hat{u}_t$$

$$\hat{b}_1 = (\hat{b}_{11} \ldots b_{1k}) \ni \hat{b}_{11} + \frac{1}{T}\sum_{t=1}^{T} \hat{w}_{1t}^3 \quad (21)$$

$$\hat{b}_2 = (\hat{b}_{12} \ldots . \hat{b}_{2k}) \ni \hat{b}_{12} = \frac{1}{T}\sum_{t=1}^{T} \hat{w}_{1t}^4 \quad (22)$$

Finally, our test statistics are

$$\lambda_s = \frac{T\hat{b}_1^T}{6} \quad (23)$$

$$\lambda_k = \frac{(\hat{b}_2 - 31)T(\hat{b}_2 - 31)}{24} \quad (24)$$

$\lambda_{Sk} = \lambda_S + \lambda_k$

Which have Chi-Square distributions each with varying degrees of freedom.

Forecasting

Forecasts for h-steps ahead is given as

$$Y_{T+h/T} = \boldsymbol{C} + \prod_1 Y_{T+h-1/T} + \cdots + \prod_p Y_{T+h-P/T} \quad (25)$$

where $Y_{T+j/T} = Y_{T+j}$ for j ≤ 0.

RESULTS AND DISCUSSIONS

Descriptive Analysis

In Table 1, the results show that the number of malaria cases among children ranges from 9 to 190 with a mean value of 57.7583, malaria cases among adults, ranges from 13 to 271 with a mean value of 62.4205 while malaria cases among pregnant women ranges from 2 to 91 with a mean value of 22.5596. The result indicated that malaria cases are higher among adult in Jimeta, Adamawa State. Table 2 shows the monthly descriptive statistics of number of malaria cases among children, adults and pregnant women. The datasets indicated that malaria cases increases from the months of April to August and gradually reduced from September to December.

Table 1: Descriptive Statistics of Series January 2011 to December 2020

Variables	N	Mean	Std	Min.	Max.
Children	120	57.7583	39.3875	9	190
Adult	120	98.8000	62.4205	13	271
Pregnant Women	120	27.0500	22.5596	2	91

Table 2: Monthly Descriptive Statistics of Malaria Cases Among Children, Adults and Pregnant Women

Months	Children		Adult		Pregnant Women	
	Mean	Std	Mean	Std	Mean	Std
January	18.2000	9.13844	38.5000	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	110.1000	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

Stationary Test Analysis

From Table 3, 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: Stationarity Test for Malaria Cases among Children, Adults and Pregnant Women

Series	ADF Test		P-P Test		Remark
	Test Statistic	P-Value	Test Statistic	P-Value	
Children	-4.715	0.0001	-4.496	0.0002	Stationary at level
Adult	-3.866	0.0023	-3.422	0.0102	Stationary at level
Pregnant Women	-5.779	0.0000	5.818	0.0000	Stationary at level

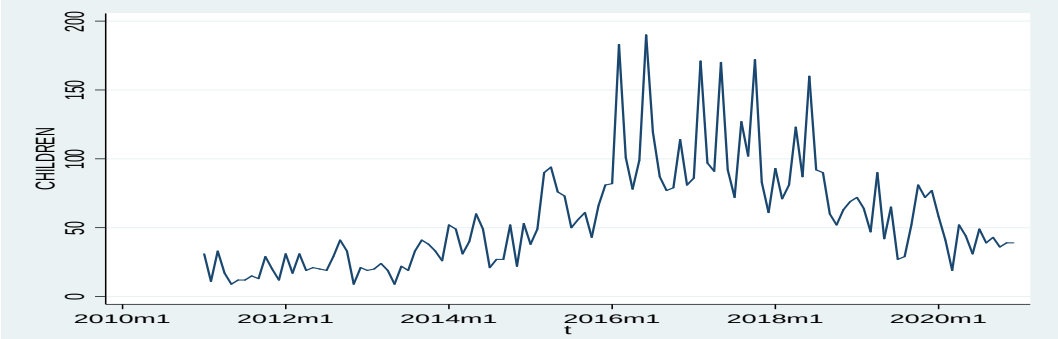

Figure 1: Monthly Time Series Plot of Malaria Cases among Children from January, 2011 to December, 2020.

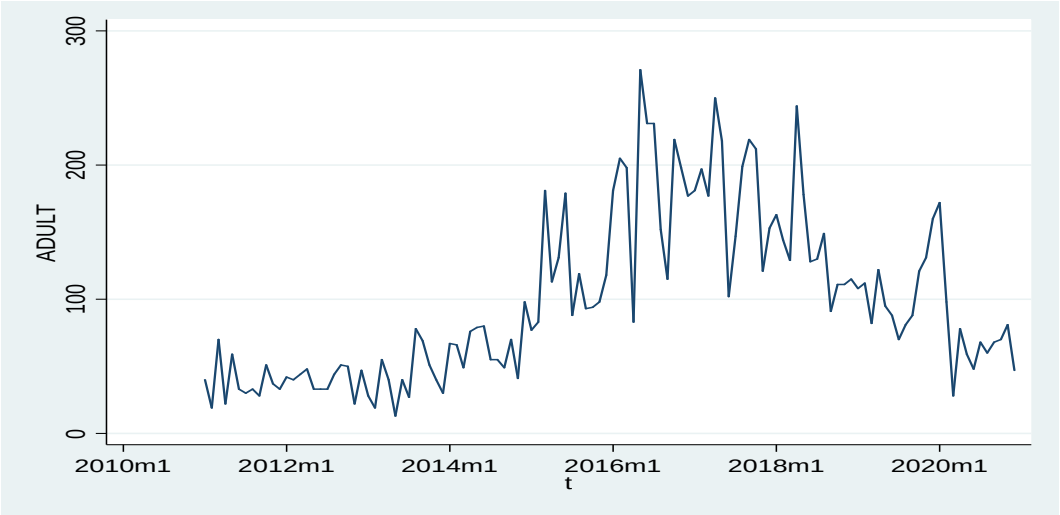

Figure 2: Monthly Time Series Plot of Malaria Cases among Adults from January, 2011 to December, 2020.

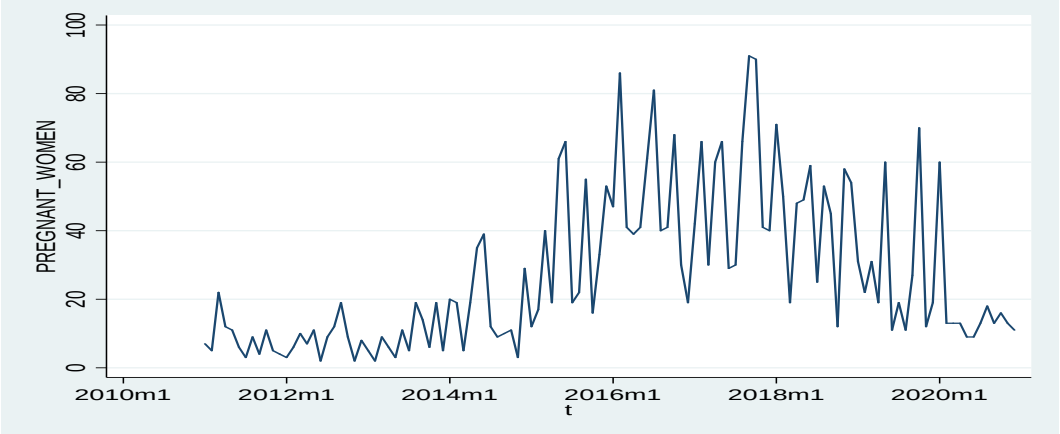

Figure 3: Monthly Time Series Plot of Malaria Cases among Pregnant Women from January, 2011 to December, 2020. Where m1 represent January of every year in Figures I to III.

The VAR Model

Table 4 shows that, the test 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 5. 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.

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 lagged values.

Table 4: Lag selection

lag	LL	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

Endogenous: children adult pregnant_women

Table 5: Modeling of Vector Auto Regressive Model

	Coef.	Std. Err.	z	P-value	95% Conf.	Interval
Children						
children						
L1.	-.081838	.122856	-0.67	0.505	-.3226313	.1589553
L2.	.0792779	.1249242	0.63	0.526	-.1655691	.3241249
L3.	.1469114	.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_women						
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	0.90	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.	.0516103	.1329969	0.39	0.698	-.2090589	.3122794
L3.	-.0441962	.1311176	-0.34	0.736	-.3011819	.2127895
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	.2242976
L2.	.1295535	.0812716	1.59	0.111	-.0297359	.2888429
L3.	.1236901	.0758526	1.63	0.103	-.0249782	.2723585
adult						
L1.	.1855702	.0502902	3.69	**0.000***	.0870032	.2841372
L2.	-.0183594	.0572219	-0.32	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	-.4413597	-.0157014
L3.	.26668	.1100576	2.42	**0.015***	.0509711	.4823888
_cons	-.708047	2.773162	-0.26	0.798	-6.143345	4.727251

The Fitted VAR (3) Model

$$\left.\begin{aligned} Y_{1t} &= 3.845 - 0.082Y_{1t-1} + 0.465Y_{2t-1} - 0.005Y_{3t-1} + 0.079Y_{1t-2} + \\ &\quad 0.034Y_{2t-2} - 0.245Y_{3t-2} + 0.147Y_{1t-3} + 0.034Y_{2t-3} - 0.008Y_{3t-3} \\ Y_{2t} &= 12.358 + 0.234Y_{1t-1} + 0.433Y_{2t-1} - 0.056Y_{3t-1} + 0.246Y_{1t-2} + \\ &\quad 0.052Y_{2t-2} - 0.459Y_{3t-2} + 0.126Y_{1t-3} - 0.044Y_{2t-3} + 0.820Y_{3t-3} \\ Y_{3t} &= -0.708 + 0.068Y_{1t-1} + 0.186Y_{2t-1} - 0.059Y_{3t-1} + 0.130Y_{1t-2} - \\ &\quad 0.018Y_{2t-2} - 0.229Y_{3t-2} + 0.124Y_{1t-3} - 0.068Y_{2t-3} + 0.267Y_{3t-3} \end{aligned}\right\} \quad (38)$$

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 suggest 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 level.

Table 6: Lagrange-Multiplier (LM) Test

lag	chi2	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	0.29367
8	10.4876	9	0.31247
9	16.2176	9	0.06247

H_0: No autocorrelation at lag order

The result for Jarque-Bera, Skewness and Kurtosis tests of residuals normality presented in Table 7 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 7: Normality test of residuals (Jarque-Bera (J-B))

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

Forecasted Result

Table 8 shows that the monthly forecasted values of malaria cases (to the nearest whole number) among children, adult and pregnant women in Jimeta of Adamawa State for the year January, 2021 to December, 2023. The forecasted values show that rates of malaria cases are higher among adult followed by children and then pregnant women.

Table 8: Monthly Forecast of Malaria Cases Among Children, Adult and Pregnant Women for the Year 2021 to 2023

Year	Months	Children	Adult	Pregnant Women
2021	January	33	64	15
2021	February	41	66	17
2021	March	39	66	18
2021	April	39	68	17
2021	May	41	71	19
2021	June	43	74	19
2021	July	44	74	19
2021	August	44	76	20
2021	September	45	78	21
2021	October	46	79	21
2021	November	47	81	21
2021	December	48	82	22

CONCLUSION

In this paper, we modeled malaria cases among children, adult and pregnant women using multivariate time series (VAR) model. The forecasted value shows that rates of malaria cases were higher among adults, followed by children, and pregnant women every month. Generally, the rate varies from month to month as cases increases every month from January, 2021 to December, 2021. Hence, we recommended that, various malaria prevention and control programs should be sustained and improved upon, this can help in reducing the burden of malaria among vulnerable groups, particularly pregnant women, children and adult living in malaria-endemic settings.

Conflict of Interest: None declared

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