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

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ABSTRACT
Sub-Saharan 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 adult, 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-Saharan 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 geostatistical 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 or more 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. Adegooye 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; Owowe 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

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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 epidemiological, health, economic and financial time series data for forecasting (Sims, 1980).

Let \( Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt}) \) denote an \((n \times 1)\) vector of variables. The VAR (p) model has the basic form (Hamilton, 1994):

\[
Y_t = C + \sum_{j=1}^{p} \Pi_j Y_{t-j} + \varepsilon_t
\]

where \( C \) is an \((n \times 1)\) vector of constants and \( \Pi_j \) is an \((n \times n)\) matrix of coefficients for \( j = 1, 2, \ldots, p \). The \((n \times 1)\) vector \( \varepsilon_t \) is a vector of white noise, where

\[
E(\varepsilon_t) = 0 \quad \text{and} \quad \text{Var}(\varepsilon_t) = \Sigma
\]

with \( \Sigma \) an \((n \times n)\) symmetric positive definite matrix.

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

\[
\begin{align*}
Y_{1t} &= B_{01} + B_{11} Y_{t-1} + B_{12} Y_{2t-1} + B_{13} Y_{3t-1} + B_{14} Y_{4t-2} + B_{15} Y_{5t-2} + \\
& \quad + B_{16} Y_{6t-2} + B_{17} Y_{7t-3} + B_{18} Y_{8t-3} + B_{19} Y_{9t-3} \\
Y_{2t} &= B_{02} + B_{21} Y_{t-1} + B_{22} Y_{2t-1} + B_{23} Y_{3t-1} + B_{24} Y_{4t-2} + B_{25} Y_{5t-2} + \\
& \quad + B_{26} Y_{6t-2} + B_{27} Y_{7t-3} + B_{28} Y_{8t-3} + B_{29} Y_{9t-3} \\
Y_{3t} &= B_{03} + B_{31} Y_{t-1} + B_{32} Y_{2t-1} + B_{33} Y_{3t-1} + B_{34} Y_{4t-2} + B_{35} Y_{5t-2} + \\
& \quad + B_{36} Y_{6t-2} + B_{37} Y_{7t-3} + B_{38} Y_{8t-3} + B_{39} Y_{9t-3}
\end{align*}
\]

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

Augmented Dickey-Fuller (ADF) Test
Consider a simple AR (1) process:

\[
Y_t = \alpha Y_{t-1} + \epsilon_t
\]

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

\[
\Delta Y_t = \alpha Y_{t-1} + \epsilon_t
\]

where \( \alpha = 0 \) and \( \Delta Y_t = Y_t - Y_{t-1} \).

\[
\hat{\alpha} = \frac{\hat{\alpha}}{SE(\hat{\alpha})}
\]

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

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

\[
\Delta Y_t = \alpha Y_{t-1} + \epsilon_t + \sum_{j=1}^{p} \Pi_j \Delta Y_{t-j} + \epsilon_t + \sum_{j=1}^{p} \Pi_j \Delta Y_{t-j}
\]

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

\[
AIC(p) = ln(\hat{\sigma}^2) + \frac{2}{T} \hat{\sigma}^2
\]

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

\[
\Pi L Y_t = C + \epsilon_t
\]

where \( \Pi = \Pi_1 L^{\pi_1} \cdots L^{p} \)

The VAR(p) is stable if the roots of

\[
\det (I_n - \Pi_1 L - \Pi_2 L^2 - \cdots - \Pi_p L^p) = 0
\]

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

\[
F = \begin{pmatrix}
I_n & \Pi_1 & \cdots & \Pi_n \\
\Pi_1 & I_n & \cdots & \Pi_{n-1} \\
\vdots & \vdots & \ddots & \vdots \\
\Pi_{n-1} & \Pi_{n-2} & \cdots & I_n
\end{pmatrix}
\]

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

\[
\mu = \Pi_1 \Pi_2 \cdots \Pi_p L^p \mu
\]

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

\[
Y_t - \mu = \Pi_1 (Y_{t-1} - \mu) + \Pi_2 (Y_{t-2} - \mu) + \cdots + \Pi_p (Y_{t-p} - \mu) + \epsilon_t
\]

where \( D_t = \Pi_1 \Pi_2 \cdots \Pi_p L^p \Phi D_t + G X_t + \epsilon_t \)

where \( D_t \) is an \((n \times 1)\) matrix, \( X_t \) is an \((n \times l)\) vector, \( \Phi \) and \( G \) are parameter matrices, \( E[D_t \epsilon_t] = 0 \).

Test of residual autocorrelation

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

\[
H_0: \hat{\epsilon}_{t-i} \epsilon_t = 0 \quad (i = 1, 2, \ldots, p)
\]

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

\[
Q_h = n \sum_{j=1}^{p} \hat{\delta}^2
\]

where

\[
\hat{\delta} = T^{-1} \sum_{t=p+1}^{n} \hat{\epsilon}_t \hat{\epsilon}_{t-j}
\]

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

\[
Q_n = T^{-1} \sum_{t=p+1}^{n} \hat{\epsilon}_t \hat{\epsilon}_t
\]

instead of the original version (19).

Jarque-Bera Test (Normality of the Residuals)

The hypothesis is as presented below

\[
H_0: E(\hat{\epsilon}_t^4) = 0 \quad \text{skewness} \quad \text{and} \quad E(\hat{\epsilon}_t^6) = 3 \quad \text{Kurtosis}
\]
Hc: E(u1T) ≠ 0 or E(u2T) ≠ 3(Kurtosis)  \hspace{1cm} (19)

Formulation of the Jarque-Bera test uses a mean adjusted form of the VAR (p) model
\[ u_t = (y_t - \bar{y}) - A_1(y_{t-1} - \bar{y}) - ... - A_p(y_{t-p} - \bar{y}) \]  \hspace{1cm} (20)

let \( \hat{p} \) be the matrix satisfying \( \hat{p} \hat{p}^T = \Sigma_u \) such that \( \text{plim}(\hat{p} - p) = 0 \)

Now we define the standardized residuals and their sample moments
\[ \hat{w}_t = \hat{p}^{-1} \hat{u}_t, \]

\[ \hat{b}_1 = (\hat{b}_{11} \ldots \hat{b}_{1k}) \in \hat{B}_1 + \frac{1}{T} \sum_{t=1}^{T} \hat{w}_t^3 \]  \hspace{1cm} (21)

\[ \hat{b}_2 = (\hat{b}_{21} \ldots \hat{b}_{2k}) \in \hat{B}_2 = \frac{1}{T} \sum_{t=1}^{T} \hat{w}_t^4 \]  \hspace{1cm} (22)

Finally, our test statistics are
\[ \lambda_s = \frac{T \hat{B}_1^r}{6} \]  \hspace{1cm} (23)

\[ \lambda_k = \frac{(\hat{b}_2 - 3)}{T} \hat{B}_2 - 3 \]

\[ \lambda_{sk} = \lambda_s + \lambda_k \]  \hspace{1cm} (24)

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 Mean | Children Std | Adult Mean | Adult Std | Pregnant Women Mean | Pregnant Women 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   | 53.78021  | 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 |
|--------------|----------|----------|
|              | Test Statistic | P-Value | Test Statistic | P-Value | Remark              |
| Children     | -4.715   | 0.0001   | -4.946   | 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 |

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.

Forecasting

Forecasts for h-steps ahead is given as
\[ Y_{t+h+j/T} = C + \Pi_1 Y_{t+h-1/T} + \cdots + \Pi_p Y_{t+h-p/T} \]
where \( Y_{T+j/T} = Y_{T+j} \) for \( j \leq 0 \).

Which have Chi-Square distributions each with varying degrees of freedom.
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 | 121.71 | 9  | 0.000 | 1.1e+08 | 27.9264 |
| 1   | -1447.43 | 11.806 | 9  | 0.224 | 1.2e+08 | 27.0838 |
| 2   | -1425.07 | 32.907 | 9  | 0.000 | 1.0e+08* | 26.9458* |
| 3   | -1421.76 | 6.6312 | 9  | 0.675 | 1.1e+08 | 27.0510 |
| 4   | -1414.28 | 14.945 | 9  | 0.092 | 1.2e+08 | 27.0793 |
| 5   | -1411.86 | 4.8445 | 9  | 0.848 | 1.3e+08 | 27.2011 |
| 6   | -1408.45 | 6.8155 | 9  | 0.656 | 1.5e+08 | 27.3047 |
| 7   | -1398.58 | 19.745 | 9  | 0.020 | 1.5e+08 | 27.2885 |
| 8   | -1391.41 | 14.333 | 9  | 0.111 | 1.5e+08 | 27.3225 |
| 9   | -1387.13 | 8.557  | 9  | 0.479 | 1.7e+08 | 27.4099 |
| 10  | -1382.81 | 8.6472 | 9  | 0.470 | 1.9e+08 | 27.4965 |
| 11  | -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

#### Children

|       | Coef.    | Std. Err. | z    | P-value | 95% Conf. Interval |
|-------|----------|-----------|------|---------|--------------------|
|       |          |           |      |         |                    |
| L1.   | -.081838 | .122856   | -.67 | 0.505   | -.3226313 .1589553 |
| L2.   | .0792779 | .1249242  | .63  | 0.526   | -.1655691 .3241249 |
| L3.   | .1469114 | .169546   | 1.26 | 0.208   | -.0816098 .3754326 |
| adult |          |           |      |         |                    |
| L1.   | .4653475 | .0773021  | 6.02 | 0.000*  | .3138381 .6168568 |
| L2.   | .0339745 | .087957   | .39  | 0.699   | -.1384181 .2063672 |
| L3.   | .0336252 | .0867141  | .39  | 0.698   | -.1363314 .2035818 |
| _cons | 3.845261 | 4.262685  | .90  | 0.367   | -4.509448 12.19997 |

#### Adult

|       | Coef.    | Std. Err. | z    | P-value | 95% Conf. Interval |
|-------|----------|-----------|------|---------|--------------------|
|       |          |           |      |         |                    |
| L1.   | .2337037 | .185765   | 1.26 | 0.208   | -.1303919 .5977993 |
| L2.   | .2459947 | .188938   | 1.30 | 0.193   | -.1242304 .6162197 |
| L3.   | .1257458 | .1762988  | .71  | 0.476   | -.2197935 .471285 |
| adult |          |           |      |         |                    |
| L1.   | .4325729 | .116886   | 3.70 | 0.000   | .2034806 .6616651 |
| L2.   | .0516103 | .1329669  | .39  | 0.698   | -.2090589 .3122794 |
| L3.   | -.0041962| .1311176  | -.34 | 0.736   | -.3011819 .2127895 |
| _cons | 12.35782 | 6.445465  | 1.92 | 0.055   | -.2750636 24.99069 |

#### Pregnant_Women

|       | Coef.    | Std. Err. | z    | P-value | 95% Conf. Interval |
|-------|----------|-----------|------|---------|--------------------|
|       |          |           |      |         |                    |
| L1.   | .0676454 | .0799261  | .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.   | -.0183459| .0572219  | -.32 | 0.748   | -.1305124 .0937935 |
| L3.   | -.0678943| .0564134  | 1.20 | 0.229   | -.1784624 .0426739 |
| _cons | -.0589954| .1089904  | 0.54 | 0.588   | -.2726126 .1546217 |
| L2.   | -.2285306| .1085883  | 2.10 | 0.035   | -.4413597 .0157014 |
| L3.   | .26668   | .1105576  | 2.42 | 0.015*  | .0509711 .4823888 |
| _cons | -.708047 | 2.773162  | -0.26| 0.798   | -6.143345 4.727251 |
The Fitted VAR (3) Model

\[
Y_{1t} = 3.845 - 0.082Y_{1t-1} + 0.465Y_{2t-1} - 0.005Y_{3t-1} + 0.079Y_{1t-2} + 0.034Y_{2t-2} - 0.245Y_{2t-3} + 0.147Y_{1t-3} + 0.034Y_{2t-3} - 0.008Y_{3t-3} \\
Y_{2t} = 12.358 + 0.234Y_{1t-1} + 0.433Y_{2t-1} - 0.056Y_{3t-1} + 0.246Y_{1t-2} + 0.052Y_{2t-2} - 0.459Y_{2t-3} + 0.126Y_{1t-3} - 0.044Y_{2t-3} + 0.820Y_{3t-3} \\
Y_{3t} = -0.708 + 0.068Y_{1t-1} + 0.186Y_{2t-1} - 0.059Y_{3t-1} + 0.130Y_{1t-2} - 0.018Y_{2t-2} - 0.229Y_{2t-3} + 0.124Y_{1t-3} - 0.068Y_{2t-3} + 0.267Y_{3t-3}
\]

(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  |

H₀: 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.

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REFERENCES
Abah, A.E. and Temple, B. (2017). Prevalence of Malaria Parasite among Asymptomatic Primary School Children in Angiama Community, Bayelsa State, Nigeria. Trop Med Surg 4:203 doi:10.4172/2329-9088.1000203 https://doi.org/10.4172/2329-9088.1000203.

Abeku, T. A., De-Vlas, S. J., Borbboom, G., Teklehaiamanot, A., Kebede, A., Olana, D., Ol Oortmansen G. J. & Habbema, J. D. F. (2002). Forecasting malaria incidence from historical morbidity patterns in epidemic-prone areas of Ethiopia: a simple seasonal adjustment method performs best. Tropical medicine and international Health 10(7): 851-857

Adetunji, A.O., Fumuyiwa, F.G., and Aliyu, F.A.(2014). Properties for Sourcing Nigerian Larvicidal Plants, Molecules, 19: 8363-8372 https://doi.org/10.3390/molecules19068363

Adetunji, A.A. and Tukur A.L. (eds.) (1999) Climate “I and II” in Adamawa State in Maps, Paraclete Publisher, Yola Pp20-26.

Adegboyee A., Al-Saghir M. O. And Leung D. H. Y. (2016). Joint spatial time-series epidemiological analysis of malaria and cutaneous leishmaniasis infection, Cambridge University Press. Epidemiol. Infect., 145, 685–700. doi:10.1017/S0950268816002764

Adenonom, M. O. and Evans, O. P. (2014) Modeling the prevalence of malaria in Niger State: An application of Poisson regression and negative binomial regression models International Journal of Physical Sciences 2(4):061-068 http://academicresearchjournals.org/journal/ijps

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 DOI 10.1186/s12936-016-1602-1

Bassey, S.E., and Nwakaku, I.L. (2017). Prevalence of Malaria Parasitemia among Children between 1-10 Years Old Attending Federal Medical Centre, Yenagoa, Bayelsa State, Nigeria, EC Pharmacology and Toxicology, 3(2): 43-48

Cairns, A.J.G., Blake, D., Dowd, K., Coughlan, G.D., Epstein, D., and Khalaf-Allah, M. (2011). Mortality density forecasts: an analysis of six stochastic mortality models. Insurance: Mathematics and Economics, 48, 355-367.

Dougnon, T.V., Bankole, H.S., Hounmanou, Y.M.G., Echebiri, S., Atchade, P. and Mohammed, J. (2017). Comparative Study of Malaria Prevalence among Travellers in Nigeria (West Africa) Using Slide Microscopy and a Rapid Diagnosis Test, Journal of Parasitology Research https://doi.org/10.1155/2015/108707

Dowd, K., Cairns, A.J.G., Blake, D., Coughlan, G.D., Epstein, D., and Khalaf-Allah, M. (2011). A Gravity Model of Mortality Rates for Two Related Populations. North American Actuarial Journal, 15, 334-356.

Hamza, A.M., Rayyah, E.A.E. and Abukashawa, S.M.A. (2014). Molecular Characterization of Mosquitoes of Anopheles gambiae Species Complex (Diptera: Culicidae) from Sudan and Republic of Southern Sudan, Journal of Mosquito Research, 4(13): 1-10 https://doi.org/10.5376/jmr.2014.04.0013

Hussien E.H. and Yong B. (2018). Time Series Analysis and Forecasting Model for Monthly Malaria Infection by Box-Jenkins Techniques in Kass Zone, South Darfur State, Sudan, Journal of Scientific and Engineering Research, 5(9):35-42

Iribhogbe O.I. and Odoya E.M. (2020). Self-medication practice with antimalarials & the determinants of malaria treatment-seeking behavior among postpartum mothers in a rural community in Nigeria. Pharmacoepidemiology and Drug Safety, 30(4): 435-444 doi: 10.1002/pds.5178

Jarner, S.F., and Kryger, E.M. (2011). Modelling Adult Mortality in Small Populations: The SAINT Model. ASTIN Bulletin, 41; 377-418.

Johansen, S. (1988). Statistical analysis of cointegration vectors, Journal of Economic Dynamics and Control 12(1):231-254

Johansen, S. and Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration with Applications to demand for Money. Oxford Bulletin of Economics and Statistics 52:169-210

Kuwe D.A., Egemba R.C. & Torruam T.J. (2015). Modeling the transmission dynamics of malaria incidence in Nigeria. Journal of Mathematics and Computer Applications Research, 2(2): 1-16

Laari P. B., (2011): “spatial analysis of malaria epidemiology in the amanse west District Ghana”. Kwame Nkrumah University of Science and Technology, Department of geomatic Engineering, Unpublished M.sc Thesis.

Li, J.S.H., and Hardy, M.R. (2011). Measuring Basis Risk in Longevity Hedges. North American Actuarial Journal, 15, 177-200.

NPC. (2006). Population and housing census: Enumerators manual. National Population Commission (NPC), Federal Republic of Nigeria, pp: 1-16.

Owoeye, J.A., Akawa, O.B., Akinneye, J.O., Oladipupo, S.O., Akomoledie, O.E. (2016). Toxicity of Three Tropical Plants to Mosquito Larvae, Pupae and Adults, Journal of Mosquito Research, 6(16): 1-7
Sarki, A., Pukuma, M. S., Yoriyo, K. P., Kunihya, I. Z., Hafizu, M. S., Kolawole, A. A., Haruna, M. Y., & Ali, R. (2019). Study on malaria infection in pregnant women attending primary health care centres in Gombe metropolis, Gombe State, Northeast, Nigeria, FUDMA Journal of Sciences 3(4): 90–97.

Sims, C. A. (1980). Macroeconomics and Reality. Econometrica 48(1):1-48 https://doi.org/10.2307/1912017

Zhou, R., Li, J.S.-H., and Tan, K.S. (2013). Pricing mortality risk: A two-population model with transitory jump effects. Journal of Risk and Insurance, 80, 733-774.