International Research Journal of Natural and Applied Sciences
ISSN: (2349-4077)
Impact Factor- 5.46, Volume 4, Issue 12, December 2017
Website- www.aarf.asia, **Email** : editor@aarf.asia , editoraarf@gmail.com

DETERMINANTS OF MALARIA TRANSMISSION SYNDROME IN NIGERIA: APPLICATION OF COINTEGRATION AND CAUSALITY ANALYSIS.

David Adugh Kuhe[1] & Emmanuel Terese Azua[2]

[1]Department of Mathematics/Statistics/Computer Science, University of Agriculture, P.M.B. 2373, Makurdi, Benue State-Nigeria

[2]Department of Biological Sciences, University of Agriculture, Makurdi, Benue State-Nigeria

ABSTRACT

Climatic factors greatly influence the pattern and level of malaria transmission in Nigeria, Africa and the world. Non-climatic factors such as the type of vector, the type of parasite, environmental development and urbanization, population movement and migration, the level of immunity to malaria in human hosts, insecticide resistance in mosquitoes, and drug resistance in parasites, all have a role in affecting the severity and incidence of malaria transmission. This study is an attempt to explore the short term and long term relationship between malaria infection and climatic factors such as annual rainfall, maximum temperature, relative humidity, precipitation and wind speed in Nigeria. The study uses annual data on these variables from 1970 to 2015. Augmented Dickey-Fuller unit root test, Johansen cointegration test, fully modified least squares regression, error correction model and Granger causality test based on Toda-Yamamoto procedure are employed to study the relationship among the variables. The results indicate that all variables are integrated of order one I(1) and hence cointegrated. This confirms the existence of a stable long run or equilibrium relationship among the study variables. The FMOLS has identified rainfall, maximum temperature and relative humidity as *the main factors responsible for malaria transmission in Nigeria in the long-run. The error correction model has identified a sizeable speed of adjustment by 81.46% of disequilibrium correction annually for attaining long run equilibrium steady state position. The result of Granger causality test indicates that malaria transmission in Nigeria is Granger caused by rainfall, maximum temperature, relative humidity and precipitation.*

KEYWORDS: Anopheles Mosquitoes; Malaria Incidence; Error Correct Model; Granger Causality.

INTRODUCTION

Climate is a basic factor in determining the dynamics and distribution of malaria infection. The vector-borne disease arises from reproductive number of malaria parasites introduced into a population of susceptible hosts (Rogers and Randolph, 2000). Malaria is a serious disease caused by protozoa (*plasmodium*). The disease is transmitted by the anopheles mosquito. The female mosquito bites an infected human and sucks the blood into its stomach to start a recurring cycle of transmission (Azua *et al.,* 2009).

Seasonal or spatial changes in the environment result to climatic changes. Climate, a physical component of the environment is an important modifier of variability in breeding activity of the anopheles mosquito and distribution of pathogens that transmits malaria. It has been established that inter-annual and inter-decadal climate variability will give more light on vector-borne disease in a given area (Srinivasulu *et al.,* 2013). Kumar *et al.* (2014) has reported malaria as a public health problem in developing countries. This, they attributed to changing environmental and climatic conditions which make the fight against the scourge of malaria infection almost impossible. Azua *et al.* (2009) attributed malaria to one of the leading cause of infectious diseases as the development of drug resistant plasmodium species and insecticide resistant mosquitoes still persist. They concluded that if malaria cases are forecasted, appropriate resources will be targeted to prevent and treat the disease. This gives room for planning in order to eliminate the scourge eventually.

WHO (2004) estimated that 90% of the global pattern of malaria is attributed to environmental factors. The most needed effects of climate on vector-borne diseases such as malaria was observed in places where the disease was newly introduced and was at the edges of the vector range, and where the population have built little immunity against malaria (Odongo-Aginya *et al.*, 2015). Haque *et al.* (2010) reported that malaria is the most important tropical and parasitic disease in the world. They linked changes in malaria incidence with patterns of rainfall, temperature, humidity, precipitation and wind speed. Gomez-Elipe *et al*. (2007) related malaria incidence in a particular month to rainfall, temperature and relative humidity.

Gupta (1996) proved a strong positive association between the incidence of *plasmodium falciparum* malaria and rainfall as malaria epidemiology is dependent on medium for aquatic stages of the mosquito's life. Rainfall has been proven to increase the relative humidity and precipitation rate necessary for mosquito's survival while wind speed is related to the rate of mosquito's distribution (Briet *et al*., 2008). In some places, seasonal malaria transmission is reported with peaks just and after the rainy season (WHO, 2014). Gillies (1998) reported high incidence of malaria cases in the rainy season and attributed this to increase in the number of breeding sites. Rainfall is considered to be a major factor influencing malaria cases in Africa and a causal relationship between rainfall and malaria transmission was well recognized (Abeku, 2007). Manyi *et al.* (2015) discovered that rainfall had visible effect on mosquito vector population in Makurdi (Nigeria) with a strong positive correlation throughout the study period. Kuhe and Jenkwe (2015) investigated the causal relationship between anopheles mosquito population and climatic factors such as temperature, rainfall and relative humidity in Makurdi (Nigeria). They found a strong negative and significant relationship between anopheles mosquitoes' population and temperature whereas a strong positive and significant relationship existed between anopheles mosquito population with rainfall and relative humidity. The study established the existence of a long-run relationship between anopheles mosquito population and rainfall, temperature and relative humidity and concluded that anopheles mosquito population in Makurdi is Granger caused by rainfall, temperature and relative humidity.

The role of temperature on poikilothermic vectors as it influence malaria epidemiology have been investigated. Srinivasulu *et al.* (2013) observed these vectors at 18-26^{o}C and discovered that a change at only 1^{o}C can affect a mosquito's life span by more than one week. This they relate to the complex interaction between the plasmodium parasites, anopheline mosquitoes and humans. Water temperature is also reported to regulate the duration of aquatic breeding cycle of the mosquito vectors as it influences its longevity (Thomas and Blandford, 2013). Paaijmans *et al.* (2009) observed diurnal temperature fluctuation as having the potential to dramatically alters the rate of parasite development and hence malaria transmission. They demonstrated that diurnal temperature fluctuation around means >21^{o}C slows parasite development compared with constant temperatures, whereas, fluctuations around <21^{o}C speeds development. They concluded that models which ignore diurnal variation overestimate malaria risk in warmer environments and underestimate risk in cooler environments.

Relative humidity of less than 60% is reported to be optimal for anopheles to survive long enough to acquire and transmit malaria parasites. Manyi *et al.* (2015) reported relative humidity range of 44% to 86% and established its proportionality to rainfall in Makurdi, a mosquito infested area in North central Nigeria.

This study contributes and extends the existing literature by determining the role of climatic factors such as mean annual rainfall, maximum temperature, relative humidity, precipitation and wind speed on malaria transmission in Nigeria by employing more sophisticated statistical tools using more recent data.

MATERIALS AND METHODS

Data Sources

The data used in this work are secondary annual data covering the fiscal year 1970 to 2015. The data on malaria infection are obtained as secondary data from WHO report on malaria, (2010) and from www.kff.org/../malaria_cases/. The data on rainfall, relative humidity, maximum temperature, precipitation and wind speed were obtained from the Nigeria Metrological Agency's website.

Methods of Data Analysis

The following methods are employed in the statistical analysis of this research work:

Augmented Dickey-Fuller (ADF) Unit Root Test

Unit root test is a statistical test that converts non-stationary series to stationary series. It shows the order of integration requires rendering a series stationary. Cointegration test can only be conducted on variables which are integrated of the same order. Let $\{Y_t\}$ be a given time series, the ADF unit root test is used to check whether the given series contains a unit root or whether the given series is stationary or not, Dickey and Fuller (1979).

The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR(p) process and adding lagged difference terms of the dependent variable to the right-hand side of the test regression:

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + \varepsilon_t \quad (2.1)$$

where X_t are optional exogenous regressors which may consist of constant, or a constant and trend, α and δ are parameters to be estimated, and the ε_t are assumed to be white noise. The null and alternative hypotheses are written as:

$$H_0: \alpha = 0 \text{ vs } H_1: \alpha < 0 \quad (2.2)$$

and evaluated using the conventional t −ratio for α:

$$t_\alpha = \hat{\alpha}/\{\mathrm{se}(\hat{\alpha})\} \quad (2.3)$$

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

An important result obtained by Fuller is that the asymptotic distribution of the t −ratio for α is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that Y follows an autoregressive (AR) process may seem restrictive, Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression. For more detail of the ADF test see [Davidson and MacKinnon, 1993, Chapter 20, Hamilton, 1994, Chapter 17, and Hayashi, 2000, Chapter 9].

Johansen Cointegration Test

Let $\{Y_t\}$ be a given time series, a Vector Autoregressive based cointegration test methodology developed by Johansen (1991, 1995) is given below. Consider a VAR of order p:

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + BX_t + \varepsilon_t \quad (2.4)$$

where $Y_t =$ k-vector of non-stationary I(1) variables; $X_t =$ d-vector of deterministic variables and ε_t = a vector of innovations. We may rewrite this VAR as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + BX_t + \varepsilon_t \quad (2.5)$$

where

$$\Pi = \sum_{i=1}^{p} A_i - \boldsymbol{I}, \ \Gamma_i = -\sum_{j=i+1}^{p} A_j \quad (2.6)$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank $r < k$, then there exist $k \times r$ matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' Y_t$ is I(0). r is the number of cointegrating relations (the cointegrating rank) and each column of β is the cointegrating vector. Johansen cointegration test computes two statistics: trace statistic and maximum eigenvalue statistic. We only employ the trace test statistic in this paper. The trace statistic for the null hypothesis of r cointegrating relations is computed as:

$$LR_{tr}(r|k) = -T\sum_{i=r+1}^{k}\log(1-\lambda_i) \tag{2.7}$$

Model Specification

Having established that the variables under review are cointegrated, we estimate cointegrating regression equation for the variables. The residuals of the cointegrating regression will be obtanined and used for the error correction model. To specify a model describing a long-term relationship existing among the study variables, we specify Malaria infection as a function of rainfall, mean temperature, relative humidity, precipitation and wind speed. It is expressed mathematically as:

$$MI = f[RF, MT, RH, PP, WDS] \tag{2.8}$$

Since the six variables have different units of measurement, we transform them to natural logarithms. This converts them to a common unit and stabilizes their variances as well. Our model now becomes:

$$lnMI_t = \beta_0 + \beta_1 lnRF_t + \beta_2 lnMT_t + \beta_3 lnRH_t + \beta_4 lnPP_t + \beta_5 lnWDS_t + \varepsilon_t \tag{2.9}$$

where $lnMI_t$ represents natural log of malaria infection at time t, $lnRF_t$ represents natural log of rainfall at time t, $lnMT_t$ represents natural log of mean temperature at time t, $lnRH_t$ represents natural log of relative humidity at time t, $lnPP_t$ represents natural log of precipitation at time t, $lnWDS_t$ represents natural log of wind speed at time t, ε_t is the error term assumed to be normally and independently distributed with zero mean and constant variance, which captures all other explanatory variables that influence malaria infection but are not captured in the model. β_0 is the intercept of the regression model which represents the predictive value of the dependent variable when all the independent variables are kept constant. β_1, $\beta_2, \beta_3, \beta_4, \beta_5$ are the partial elasticity of malaria infection with respect to $lnRF_t, lnMT_t, lnRH_t, lnPP_t, lnWDS_t$ respectively.

The Error Correction Model (ECM)

The one period lagged error correction model, which integrates short-run dynamics in the long-run relationship given by:

$$\Delta lnMI_t = \alpha_1 + \sum_{i=1}^{p}\beta_{2i} lnMI_{t-1} + \sum_{i=0}^{p}\gamma_{3i}\Delta lnRF_{t-1} + \sum_{i=0}^{p}\phi_{4i}\Delta lnMT_{t-1}$$

$$+\sum_{i=0}^{p}\varphi_{5i}\Delta lnRH_{t-1}+\sum_{i=0}^{p}\theta_{6i}\Delta lnPP_{t-1}+\sum_{i=0}^{p}\delta_{7i}\Delta lnWDS_{t-1}+\lambda_{8}EC_{t-1}+\varepsilon_{2t} \qquad (2.10)$$

where EC_{t-1} is the error correction term (the residuals that are obtained from the estimated cointegrating model of equation (3.9)). It is the feedback and adjustment effect which indicates how much of the disequilibrium is being corrected. It proves the stability of the long-run relationship when it is negative and highly statistically significant (Bannerjee, *et al.* 1998). ε_{2t} is the error term. The symbol Δ represents the first-differenced form of the variables in the model. The coefficient of the various explanatory variables, $\beta_{2i}, \gamma_{3i}, \phi_{4i}, \varphi_{5i}, \theta_{6i}, \delta_{7i}$ are the impact multipliers that measure the immediate impact that a change in the explanatory variable has on a change in the dependent variable. λ represents the speed of the adjustment parameter. The value of λ must lie between the range $-1 \leq \lambda \leq 0$ and must be statistically significant.

When variables are cointegrated, there is a long term or equilibrium relationship between them. This means that in the short run there may be disequilibrium. Therefore, we can treat the error term obtained from cointegrating regression equation as the equilibrium error. This error term can be used to tie the short-run behaviour of the dependent variable (malaria infection) to its long-run value. The error correction model (ECM) corrects for disequilibrium. This is in accordance with the Granger Representation theorem which states that *"if two variables X and Y are cointegrated, then the relationship between the two can be expressed as ECM"* (Gujarati, 2003). Since the variables under study are cointegrated, we are now in a better position to integrate short-run dynamics with long-run equilibrium. To ascertain the goodness of fit of the long run model, the diagnostic test is conducted. The diagnostic test examines the serial correlation associated with the model.

As goodness of fit tests to the estimated ECM, we employ serial correlation Lagrange multiplier test, the heteroskedasticity ARCH test, Ramsey RESET test, Jarque-Bera normality test and Q-statistic test up to lag 20 to check respectively for the presence of serial correlation in the residuals; ARCH effects in the residuals of the estimated model; whether the estimated equation was specify correctly; whether the residuals of the estimated model are normally distributed and to check the presence of autocorrelation in the residuals of the estimated ECM. We therefore accept the null hypotheses if the p-values of the tests are greater than 0.05 and reject if otherwise.

Granger Causality based on Toda-Yamamoto Procedure

This section focuses on the direction of causality between malaria infection and climatic variables used in this study. Since cointegration test do not tell us the direction of the relationship between variables, we conduct Granger causality test based on Toda-Yamamoto procedure. To conduct Granger causality test based on Toda-Yamamoto procedure, we set up a 2-equation VAR model in the levels of the data, including an intercept in each equation. Toda and Yamamoto (1995). Toda and Yamamoto procedure uses a Modified Wald (MWALD) test for restrictions on the parameters of the VAR (k) model. The advantage of using this procedure is that it is not necessary to pretest the variables for the integration and cointegration properties and therefore, it avoids the possible pretest biases. The model is specified as follows:

$$Y_t = \alpha_1 + \sum_{i=1}^{k+d} \gamma_{1i} Y_{t-i} + \sum_{t-i}^{k+d} \gamma_{2i} X_{t-i} + \varepsilon_{yt} \qquad (2.11)$$

$$X_t = \alpha_2 + \sum_{i=1}^{k+d} \delta_{1i} Y_{t-i} + \sum_{t-i}^{k+d} \delta_{2i} X_{t-i} + \varepsilon_{xt} \qquad (2.12)$$

Where $k =$ optimal lag order; $d =$ maximal order of integration of the series in the system; ε_{yt} and ε_{xt} are error terms which are assumed to be white noise. Usual Wald tests are then applied to the first k coefficient matrices using the standard χ^2-statistics. The test checks the following pairs of hypotheses: X_t "Granger causes" Y_t if $\gamma_{2i} \neq 0$ in equation (2.11) against Y_t "Granger causes" X_t if $\delta_{1i} \neq 0$ in equation (2.12)

RESULTS AND DISCUSSION

Unit Root Test Result

To determine the order of integration of the study variables, we employ Augmented Dickey-Fuller (ADF) unit root test both in levels and first differences of the series. The ADF unit root test result is presented in Table 1.

TABLE 1: ADF Unit Root Test Result

	lnMI	lnMT	lnRF	lnRH	lnPP	lnWDS
Level	-1.5478	-0.9514	-2.0356	-1.7549	-1.0394	-1.4431
1^{st} Diff.	-6.6544**	-5.7546**	-6.3636**	-7.3649**	-7.0933**	-7.2532**

Note: ** denotes significant of the ADF test statistic at 1% and 5% level of significance

The results indicate that all the variables under consideration: malaria infection, maximum temperature, rainfall, relative humidity, precipitation and wind speed, are non-stationary in levels, but stationary in their first differences. Thus, we conclude that all the variables under review are integrated of order one, I(1).

Johansen Cointegration Test Results

Having established that the variables under investigation are integrated of the same order, we are now in a better position to explore their long-term relationships using Johansen cointegration test procedure. The result of the Trace test is reported in Table 2.

TABLE 2: Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	H_0	H_1	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	$r = 0$	$r \geq 0$	0.6251	159.5773	107.3466	0.0000
At most 1 *	$r \leq 1$	$r \geq 1$	0.5630	116.4146	79.3415	0.0000
At most 2 *	$r \leq 2$	$r \geq 2$	0.5084	79.9907	55.2458	0.0001
At most 3 *	$r \leq 3$	$r \geq 3$	0.4413	48.7487	35.0109	0.0010
At most 4 *	$r \leq 4$	$r \geq 4$	0.2972	23.1324	18.3977	0.0101
At most 5 *	$r \leq 5$	$r = 5$	0.1589	7.61385	3.8415	0.0058

Note: Trace test indicates 6 cointegrating equations at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level. ** denotes MacKinnon-Haug-Michelis (1999) p-values.

The statistical hypotheses of no cointegration are rejected for the trace test statistic. The trace test indicates six cointegrating equations at the 0.05 significance level. This confirms the existence of a stable long run or equilibrium relationship among malaria infection, rainfall, maximum temperature, relative humidity, precipitation and wind speed. What this long run relationship means is that the variables under study share a common stochastic drift. This also means that the variables will not wander away from each other.

Cointegrating Regression Equation Results

The result of the cointegrating regression equation is presented in Table 3.

TABLE 3: FMOLS Estimates of Cointegrating Regression Equation

Dependent Variable: lnMI		Method: Fully Modified Least Squares (FMOLS)		
Variable	Coefficient	Std. Error	t-Statistic	P-value
C	15.74066	10.04988	2.063771	0.0457
lnRF	0.872389	11.19978	3.727121	0.0015
lnMT	0.445227	9.010589	1.991441	0.0259
lnRH	0.293809	10.74558	-4.480473	0.0468
lnPP	0.046836	0.612047	0.076523	0.9394
lnWDS	-0.672984	0.476586	1.412094	0.1659
R-squared				0.7693
Adjusted R-squared				0.6281
Durbin-Watson stat				2.0456

The output of multiple cointegrating regression analysis describes the long-run relationship between malaria transmission and climatic variables in Nigeria. The result shows that the constant parameter (the intercept) is positively related to malaria infection and statistically significant implying that the predicted value of malaria infection in Nigeria will be 15.74066 units (representing 6 856 173 people) if all the explanatory variables are held constant. The slope coefficients of rainfall (lnRF), maximum temperature (lnMT), and relative humidity (lnRH) which are significant at 5 percent levels are positively related with malaria infection in Nigeria. This implies that a one percent increase in rainfall, maximum temperature and relative humidity will increase the transmission rate of malaria in Nigeria by 87.24%, 44.52% and 29.38% respectively. This is true because anopheline mosquitoes breed in water and the right amount of rainfall is often important for them to breed. Different anopheline mosquitoes prefer different types of water bodies in which to breed. Water collections that support vector breeding appear mainly after the rains, and therefore malaria transmission is highest following the rainy season. The ranges of minimum and maximum temperature greatly affect the development of the malaria parasite and its mosquito vector, which determines malaria transmission. The mosquito larva develops more quickly as the temperature increases. Higher temperatures also increase the number of blood meals taken by mosquitoes and the number of eggs lay which increases the number of mosquitoes in a given area. Also, mosquitoes survive better under conditions of high humidity. They also become more active when humidity rises. This is why they are more active and prefer feeding during the night because the relative humidity of the environment is higher at night.

The slope coefficient of precipitation (lnPP) is positive though not statistically significant showing that a positive relationship exists between malaria transmission and precipitation. This means that a one percent increase in precipitation will lead to 4.68% increase in malaria infection. The slope coefficient of wind speed (lnWDS) is negative and statistically insignificant indicating a negative relationship between malaria infection and wind speed. That is, for every 1% increase in wind speed, the infection rate of malaria in Nigeria is predicted to decline by 67.29%. This is true because higher wind speed destabilizes the malaria vector thereby reducing its concentration on the human host and consequently retarding the transmission rate.

The coefficient of determination (R^2) of the cointegrating regression model is 0.7693 indicating that about 76.93% of the total variations in malaria infection in Nigeria have been explained by the regression model while the remaining 23.07% unexplained variations is being accounted for by the error term or by factors not included in the model. The Durbin Watson statistic value of 2.0456 which is greater than R^2 and R^2 adjusted means that the model is non-spurious. In the long-run, this study has identified rainfall, maximum temperature and relative humidity as the determinants of malaria infection and transmission in Nigeria.

Error Correction Model (ECM)

Table 4 shows the output of the Error Correction Mechanism.

TABLE 4: OLS Parameter Estimates of Error Correction Model

Dependent Variable: ΔlnMI		Method: Ordinary Least Squares (OLS)		
Variable	Coefficient	Std. Error	t-Statistic	P-value
C	0.038390	0.123072	0.311928	0.7569
ΔlnMI(-1)	-0.105965	0.199815	-0.530315	0.5991
ΔlnRF(-)	0.383113	1.024882	2.373812	0.0107
ΔlnMT(-1)	-0.636012	1.804643	-3.352431	0.0266
ΔlnRH(-1)	0.843661	0.640113	4.317988	0.0028
ΔlnPP(-1)	-0.437422	0.512211	-0.853989	0.3988
ΔlnWDS(-1)	-0.205720	0.436310	-0.471499	0.6401

EC(-1)	-0.814612	0.262975	-3.097682	0.0038
R-squared				0.7651
Adjusted R-squared				0.6611
Durbin-Watson stat				2.0301
F-statistic	4.471493	Probability (F-statistic)		0.0012

The estimated result of the ECM shows that the model is non-spurious as the DW statistic is greater than R^2 statistic. The slope coefficients of ΔlnMI(-1), ΔlnRF, ΔlnMT, ΔlnRH, ΔlnPP and ΔlnWDS represent the short run equilibrium coefficients while the slope coefficient of EC(-1) is the long run equilibrium coefficient which is known as the error correction coefficient. It is negative and significant as expected.

The estimated slope coefficients of ΔlnRF, ΔlnMT and ΔlnRH are statistically significant at 5% level. The estimated slope coefficients of ΔlnMI(-1), ΔlnPP and ΔlnWDS are statistically insignificant at 5% level. These coefficients represent the short run coefficients as well as the short run equilibrium. They tell us about the rates at which the previous period's disequilibrium of the system is being corrected. The slope coefficients of ΔlnMI(-1), ΔlnRF, ΔlnMT, ΔlnRH, ΔlnPP and ΔlnWDS indicate that the system corrects its previous period disequilibrium at the speed of 10.60% between malaria infection and malaria infection lag one year, 38.31% between malaria infection and rainfall lag one year, 63.60% between malaria infection and maximum temperature lag one year, 84.37% between malaria infection and relative humidity lag one year, 43.74% between malaria infection and precipitation lag one year and 20.57% between malaria infection and wind speed lag one year. The smaller percentages indicate how slow the variables correct previous period's disequilibrium in the system.

The one period lag error correction term or residual is represented by EC(-1). It guides the independent variables of the system (ΔlnMI(-1), ΔlnRF, ΔlnMT, ΔlnRH, ΔlnPP and ΔlnWDS) to restore back to equilibrium or corrects disequilibrium. For this to happen, the sign of its slope coefficient should be negative and significant. From the output of our estimates the slope coefficient of EC(-1) is significant at 5% level indicating that system corrects its previous period disequilibrium at a speed of 81.46% yearly. This implies that the model have identified a sizeable speed of adjustment by 81.46% of disequilibrium correction annually for attaining long run equilibrium steady state position.

ECM Model Diagnostic Checks

The results of diagnostic tests of the estimated ECM are presented in Table 5.

TABLE 5: Results of Diagnostic Checks of the Estimated ECM Equation

Type of Test		F-statistic [p-value]		nR^2 [p-value]	
Serial Correlation LM test		0.7284 [0.4900]		1.8079 [0.4050]	
Heteroskedasticity Test: ARCH		3.3140 [0.0760]		3.2157 [0.0729]	
Ramsey RESET Test		0.1304 [0.7202]		Na	
Jarque-Bera	2.4467 [0.2942]	Q(1)-stat	0.0979 [0.754]	Q(20)-stat	16.766 [0.668]

Note: na denote not applicable. Numbers in parentheses are p-values

The long-run econometric error correction model have passed all the diagnostic tests: Serial correlation LM test, heteroskedasticity ARCH test, Ramsey Regression Equation Specification Error Test (RESET) test, Jarque-Bera normality test and Ljung-Box Q-statistic test. The null hypotheses that the residuals are serially uncorrelated; there is no ARCH effect remaining in the residuals; the DECM equation is not misspecified; the errors are normally distributed, and that the residuals are not autocorrelated for the five tests respectively has been accepted since the p-values of all the five tests are strictly greater than 0.05 levels of significance. This validates our ECM model as being adequate, valid and good.

Granger Causality Test Based on Toda-Yamamoto Procedure

The various information criteria suggest that we should have a maximum lag length of 0 for each variable as indicated in Table 6.

TABLE 6: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	114.1024	NA*	1.32e-09*	-3.43345*	-1.69578*	-2.79652*
1	135.5440	29.60979	2.95e-09	-2.740189	0.486911	-1.557329
2	165.3376	32.63111	5.34e-09	-2.444647	2.271885	-0.715852
3	192.6511	22.11092	1.57e-08	-2.031004	4.174959	0.243727

Note: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

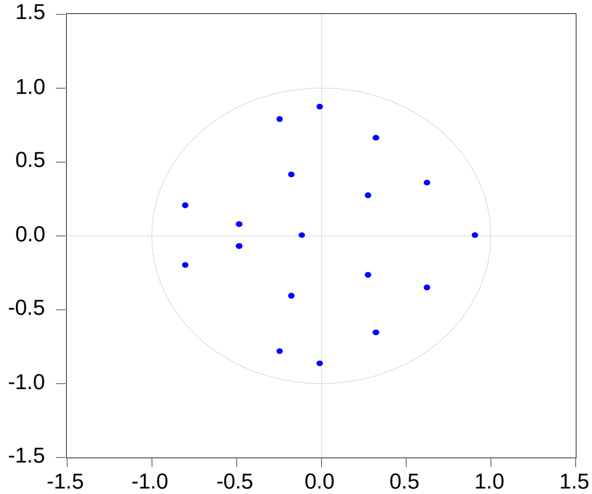

FIGURE 1: Inverse Roots of AR Characteristic Polynomial of the Estimated VAR Model

From Figure 1, we observe that the inverse roots of the AR characteristic polynomial of the estimated VAR model are all inside a unit circle. This is good evidence that the estimated VAR model is dynamically stable. Since the estimated VAR model has passed the stability test, we use it to obtain estimates for the modified Wald test. The result is reported in Table 7. The estimates of the test are standard χ^2-statistics while the values in parentheses are p-values.

TABLE 7: Granger Causality Test Results based on Toda-Yamamoto Procedure

Variable	Modified Wald Test					
	MI	RF	MT	RH	PP	WDS
MI	---	15.380	12.447	10.249	9.2079	4.3946
		[0.006]*	[0.040]*	[0.050]*	[0.052]*	[0.222]
RF	0.8134	---	1.0744	0.9709	12.058	0.1305
	[0.846]		[0.783]	[0.808]	[0.007]*	[0.988]
MT	0.9036	4.0818	---	0.6821	3.2077	0.8643
	[0.825]	[0.253]		[0.877]	[0.361]	[0.834]
RH	0.1290	11.625	1.0442	---	4.5522	1.6567
	[0.988]	[0.025]*	[0.791]		[0.207]	[0.647]
PP	5.3917	12.694	0.3125	0.1539	---	0.8207

	[0.145]	[0.041]*	[0.958]	[0.985]		[0.845]
WDS	5.1041	3.0557	3.7479	0.7273	3.2846	---
	[0.164]	[0.383]	[0.290]	[0.867]	[0.961]	

The result of Granger causality test indicates that there are one-way causalities that run from rainfall to malaria infection, maximum temperature to malaria infection, relative humidity to malaria infection and from precipitation to malaria infection. This means that transmission of malaria infection in Nigeria is Granger caused by rainfall, maximum temperature, relative humidity and precipitation. Also there is a unidirectional causality that runs from rainfall to relative humidity. This means that rainfall Granger causes relative humidity but not the other way round. There is a bilateral causality between rainfall and precipitation. The implication here is that rainfall Granger causes precipitation and precipitation in turn Granger causes rainfall. The result of Table 7 also indicates independent relationships among other variables under consideration. This implies that there are no unidirectional or bilateral causalities among other variables.

CONCLUSION AND RECOMMENDATIONS

This study has attempted to explore the short term and long term relationship between malaria infection and climatic factors such as annual rainfall, maximum temperature, relative humidity, precipitation and wind speed in Nigeria. The study used annual data on these variables from 1970 to 2015. The unit root properties of the variables was investigated using Augmented Dickey-Fuller unit root test, Johansen cointegration test was then applied to determine the relationship between variables, fully modified least squares regression and error correction model were employed to explore the long-run and short-run dynamics of the study variables and Granger causality test based on Toda-Yamamoto procedure was employed to study the direction of causality among the variables. The results indicate that all variables are integrated of order one I(1) and hence cointegrated thereby confirming the existence of a stable long run or equilibrium relationship among the study variables. The FMOLS regression has identified rainfall, maximum temperature and relative humidity as the main factors responsible for malaria transmission in Nigeria in the long-run. The error correction model has identified a sizeable speed of adjustment by 81.46% of disequilibrium correction annually for attaining long run equilibrium steady state position. The result of Granger causality test indicates that malaria transmission in Nigeria is Granger caused by rainfall, maximum temperature, relative humidity and precipitation. The Granger causality test has also identified a unidirectional causality between rainfall and relative humidity and a bilateral causality between rainfall and precipitation.

Since climatic factors such as rainfall, temperature, relative humidity, precipitation and wind speed are regulated by nature which can never be manipulated, regulated or controlled by human beings, this study strongly calls on the relevant authorities, administrators, international agencies and the Nigerian governments at all levels to collaborate and wage a strong war against malaria scourge in Nigeria. Strong preventive, curative and control measures against this vector-borne disease are highly recommended in order to reduce the rate of transmission.

REFERENCES

- Abeku TA (2007) Response to malaria epidemics in Africa. *Emerg Infect Dis* 13: 681-686
- Azua ET, Bala U & Ega RAI (2009) The significance of malaria parasites in public health (A Case study of Akwanga town, Nasarawa state) *Annals of Research in Nigeria*, 7(1): 66-74
- Bannerjee A, Dolado T & Mestre R (1998) Error correction mechanism tests for cointegration in single equation framework. *Journal of Time Series Analysis*, 19: 267-283.
- Briet J, Vounatsou P, Gunawardena D, Galappaththy N & Amerasinghe P (2008) Temporal correlation between malaria and rainfall in Sri Lanka. *Malaria Journal*, 7: 77.
- Davidson R, & MacKinnon JG (1993*)* Estimation and inference in econometrics, Oxford,
- Oxford University Press.
- Dickey DA, & Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427–431.
- Gillies MT (1988) Anopheline mosquitoes vector behaviour and bionomics in malaria: principles and practice of malariogy. 1st ed. Wernsdorfer, W.H. and McGregor, I. (Eds.), Churchhill Livingstone, pp. 453-485
- Gomez-Elipe A, Otero A, Van Herp M & Aguirre-Jaime A (2007) Forecasting malaria incidence based on monthly case reports and environmental factors in Karuzi, Burundi, 1997-2003. *Malaria Journal*, 6(1): 129
- Gupta R (1996) Correlation of rainfall with upsurge of malaria in Rajasthan. *Journal of Association of Physicians in India*, 44: 385-389.

- Hamilton JD (1994) Time Series Analysis. Princeton, NJ: Princeton University Press.
- Hayashi F (2000) Econometrics. Princeton, NJ: Princeton University Press.
- Haque U, Hashizume M, Glass EG, Dewan MA, Overgaard JH & Yamamoto T (2010) The role of climate variability in the spread of malaria in Bangladeshi highlands. *PLoS one*, 5(12): 1-9.
- Gujarati DN (2003) Basic econometrics. 4th ed. McGraw-Hill Higher Education, New York, pp. 822-825.
- Johansen S (1991) Estimation and hypothesis testing for cointegration vectors in Gausian vector autoregressive models. *Econometrica,* 59:1551-1580.
- Johansen S (1995) Likelihood-based inference in cointegrated vector autoregressive models. Oxford University Press, Oxford.
- Kuhe DA & Jenkwe ED (2015) The causal relationship between anopheles mosquito population and climatic factors in Makurdi-Nigeria: An empirical analysis. *Scientific Research Journal*. III(XI): 40-49.
- Kumar V, Mangal A, Panesar S, Yadav G, Talwar R, Ratu D & Singh S (2014) Forecasting malaria cases climatic factors in Delhi, India: A time series analysis. *Malaria Research and Treatment*, 2014:1-6
- MacKinnon JG, Haug AA & Michelis L (1999) Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, 14: 563-577.
- Manyi MM, Akaahan JT & Azua ET (2015) Relationship between weather parameters and female mosquitoes' abundance and distribution in Makurdi, a mosquito infested area in north central Nigeria. *International Journal of Sciences*, 4(6): 44-54.
- Odongo-Aginya E, Ssegwanyi G, Kategere P & Vuzi PC (2005) Relationship between malaria infection intensity and rainfall pattern in Entebbe Peninsula, Uganda. *African Health Series,* 5(3): 238-245
- Paaijmans PK, Read FA & Thomas BM (2009) Understanding the link between malaria risk and climate. *PNAS*, 106(33): 1344-1349.
- Rogers DJ & Randolph SE (2000) The global spread of malaria in a future, warmer world. Science, 289: 1763-1766
- Said SE & Dickey DA (1984) Testing for unit roots in autoregressive moving average models of unknown order. *Biometrika,* 71: 599–607.

- Srinivasulu N, Gujju GB, Naik R & Sambashiva D (2013) Influence of climate change on malaria incidence in Mahaboobnagar district of Andhra Pradesh, India, 2(5): 256-266
- Thomas M & Blanford S (2003) Thermal biology in insect-pathogen interactions. *Trends Ecological Evolution*, 18: 344-350
- Toda HY & Yamamoto T (1995) Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics,* 66(1&2): 225-250.
- WHO (World Health Organization; 2004) Malaria epidemics forecasting, prevention, early detection and control, from policy to practice. Report of an informal consultation, World Health Organization, Geneva, Switzerland, 2004.
- WHO (World Health Organization; 2014) Preventing vector-borne disease. World Health Campaigns, 2014.