MODELING THE EFFECTS OF CLIMATE VARIABILITY ON MALARIA PREVALENCE

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ABSTRACT

Malaria is believed to be one of the deadly killers of humans worldwide and a threatto one-third of the world's population. Based on this assertion, this study is used to determine the effect of Ibadan climatic variability on Ibadan malaria prevalence proportion since the city has a holoendemic malaria transmission. Multiple Trigonometric regression model was used to determine the effects of rainfall and temperature on Ibadan malaria prevalence since it can be used to model series that exhibit two or more types of variations simultaneously. From the results, the residuals of the fitted multiple trigonometric regression model are not serially correlated based on the value of the Durbin Watson Statistics. The coefficients of the fitted model were used to establish that for every unit increase or decrease in Ibadan city rainfall and temperature, there might be an increase or decrease in the malaria prevalence proportion over the years. The values of coefficient of determination (R^2) revealed that Ibadan city monthly rainfall and temperature jointly explained the variations in Ibadan malaria prevalence proportion up to 61%. The fitted multiple trigonometric regression model as well as a good fit and high predictive power based on the value of the adjusted coefficient of determination $(\bar{R}^2)$.Based on these results Multiple trigonometric regression model is suitable and adequate for modelling the effect of Ibadan monthly climatic variability on malaria prevalence proportion which can cause a high rate of morbidity and mortality if not curtailed or curbed.

Keywords: *Malaria, incidence rate, Ibadan city, Climatic variability, Trigonometric regression*

INTRODUCTION

Malaria is an ancient disease that has its existence as long as the history of human existence. It has a huge social, economic, and health burden on human and their existence (Cox, 2010). As well, it is the major tropical health challenge in the world today (Roll Back Malaria, (2005). It is the most serious health problem that affects millions of people globally and it remains a substantial public health burden with an estimated 349-552 million clinical cases of P. falciparum malaria each year--leading to 780,000 deaths directly attributable to the disease (Olupot-Olupot and Maitland, 2013). According to Roll Back Malaria (2005), malaria kills several millions of people worldwide every year. Most of this preventable death manifests in the labour force of the African region and this contributes to the serious socio-economic problems in developing countries (CDC, 2016). Transmission and prevalence of malaria are associated with changes in temperature, rainfall, humidity as well as the level of immunity (Ayansina *et al.,* 2020, Ayanlade *et al,* 2020, Ryan *et al.,* 2020). It can be as well attributed to a marked increase in the number and size of towns and cities in many developing countries (Wilson *et al.,* 2015). In particular, according to WHO Malaria Report (2019), Nigeria had the highest number of global malaria cases (25 % of global malaria cases) in 2018 and accounted for the highest number of deaths (24

% of global malaria deaths). Case numbers have plateaued at between 292 and 296 per 1000 of the population at risk between 2015 and 2018. Deaths however fell by 21% from 0.62 to 0.49 per 1000 of the population at risk during that same period (USAID, 2020).

Malaria is transmitted all over Nigeria; 76 % of the population live in high transmission areas while 24 % of the population live in low transmission areas. The transmission season can last all year round in the south and is about 3 months or less in the northern part of the country (NMIS, 2015). The burden of malaria is three times greater among rural dwellers in comparison to urban dwellerswithout a corresponding increase in services that inhibit and prevent the breeding of vectors of malaria resulting in the increase of urban malaria (Kalu, 2012).

Furthermore, several studies have established that change in climatic variables characteristics and their impacts could be better understood using statistical models. Yé *et al*., (2009) in their study emphasized that there is a strong correlation between rainfall, temperature and malaria transmission. Onyiri (2015) used Logistic regression to fit malaria prevalence and identify the significance of demographic, vegetation index, the enhanced vegetation index, the leaf area index, the land surface temperature for day and night, land use, distance to water bodies, and rainfall in the spread of malaria disease. Ibor *et al.,* (2016) analysed and fit a trend for malaria prevalence using descriptive statistics and multiple regression analysis. Their results indicated that malaria transmission is affected by rainfall and temperature. They conclude that December, January, July and February/April had the highest reported cases of malaria, while August and September had the lowest prevalence of malaria.

Alhassan *et al.,* (2017) used the autoregressive integrated moving average model to forecast malaria prevalence in Navrongo Municipality, Ghana. From their result, the monthly malaria prevalence has a constant quadratic rate with the highest malaria prevalence during peak rainfall months. Ayanlade et al, (2020) used correlation and multiple regression analysis to determine the degree of association and linear relationship between malaria prevalence, precipitation, minimum and maximum temperature. Their results indicated that rainfall has a strong correlation and direct association with the occurrence of malaria.

Ayansina *et al.,* (2020) evaluated the relationships between climatic variables and the prevalence of malaria. Their results revealed a significant positive relationship between rainfall and malaria, especially during the wet season. Despite the effort of several researchers, further investigation is required as the relationship between climatic indices and malaria prevalence keep evolving. For this reason, this study will be used to examine the relationship between variability in monthly climatic indices (rainfall and temperature) and monthly malaria prevalence in Ibadan metropolitan city with over 3.5milloins inhabitants. The third-largest city in Nigeria with all-year-round (holoendemic) malaria transmission. One of the most densely populated areas in Nigeria with a lengthy 8-month rainy season and an average of 10 rainy days per month between May and October (Brown *et al.,* 2020). Descriptive statistics will be used to describe the series and a Multiple Trigonometric regression model will be employed to the determine relationship between Ibadan climatic variables and malaria prevalence rate. This model has the capability of handling the variability usually present in climatic variables (Olatayo *et al.,* 2018).

MATERIALS AND METHOD

Trigonometric Regression Analysis

Given a simple deterministic model as

$$y = \rho\cos(\omega t - \theta) \tag{1}$$

where ρ is the amplitude, ω is the frequency and θ is the phase.

Using the compound angle formula

$\cos(A - B) = cosAcosB + sinAsinB$

Equation 1 can be further simplified as

$$y = \rho\cos\theta cos(\omega t) + \rho\sin sin(\omega t)$$

$$y = \beta\cos(\omega t) + \beta^{*}\sin(\omega t) \tag{2}$$

where $\beta = \rho cos\theta$, $\beta^{*} = \rho sin\theta$

and $\beta^2 + \beta^{*2} = \rho^2$.

In terms of (2), a trigonometric time series regression model can be expressed

$$y_t = \beta_0 + \sum_{j=0}^{p}\beta_j\cos(\omega_j t) + \sum_{j=0}^{p}\beta_j^{*}\sin(\omega_j t) + \varepsilon_t, \quad \begin{matrix} j = 1, \dots, p \\ t = 1, \dots, T \end{matrix} \tag{3}$$

where $sin\omega$ *and* $cos\omega$ are the trigonometric functions, $\omega = \frac{2\pi k}{n}$, $X_t$is the predictors, y_t is the dependent variable, $\beta_j's$ are the trigonometric coefficients and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$is the uncorrelated error term.

By substituting $t = X_t$ in (3), the multiple forms of trigonometric time series regression become

$$y_t = \beta_0 + \sum_{j=1}^{p}\beta_j cos\omega X_t + \sum_{j=1}^{p}\beta_j^{*} sin\omega X_t + \varepsilon_{t,} \begin{matrix} j = 1, \dots, p \\ t = 1, \dots, T \end{matrix} \tag{4}$$

where $X_t$are the predictors, y_t is the dependent variable and$\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$is the error term.

Ordinary Least Squares Estimation Method

Based on the trigonometric time series regression model in equation 4,

$$y_t = \beta_0 + \beta_j cos\omega X_t + \beta_j^{*} sin\omega X_t + \varepsilon_t$$

$$\varepsilon_t = y_t - \beta_0 - \beta_j cos\omega X_t - \beta_j^{*} sin\omega X_t$$

The residual sum of square becomes

$$\sum(\varepsilon_t)^2 = \sum(y_t - \beta_0 - \beta_j\cos\,\omega X_t - \beta_j^{*}\sin\omega X_t)^2 \tag{5}$$

Differentiating (5) with respect to β_0,β_j and β_j^{*}gives

$$\left.\begin{aligned} \Sigma y_t &= n\beta_0 + \beta_j\Sigma\cos\,\omega X_t + \beta_j^{*}\Sigma\sin\omega X_t \\ \Sigma(\cos\omega X_t y_t) &= \beta_0\Sigma(\cos\omega X_t) + \beta_j\Sigma(cos^2\omega X_t) + \beta_j^{*}\Sigma(\cos\omega X_t\sin\omega X_t) \\ \Sigma(\sin\omega X_t y_t) &= \beta_0\Sigma(\sin\omega X_t) + \beta_j\Sigma(\cos\omega X_t\sin\omega X_t) + \beta_j^{*}\Sigma sin^2\omega X_t) \end{aligned}\right\} \tag{6}$$

Transforming(6) into matrix form gives

$$\begin{pmatrix} \sum(y_t) \\ \sum(\cos\,\omega X_t y_t) \\ \sum(\sin\omega X_t y_t) \end{pmatrix} = \begin{pmatrix} n & \sum(\cos\,\omega X_t) & \sum(\sin\,\omega X_t) \\ \sum(\cos\,\omega X_t) & \sum(\cos^2\omega X_t) & \sum(\cos\omega t\,\sin\omega X_t) \\ \sum(\sin\,\omega X_t) & \sum(\cos\omega X_t\sin\omega)X_t & \sum(\sin^2\omega X_t) \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_j \\ \beta_j^{*} \end{pmatrix} \tag{7}$$

$$\begin{pmatrix} \beta_0 \\ \beta_j \\ \beta_j^{*} \end{pmatrix} = \begin{pmatrix} n & \sum(\cos\,\omega X_t) & \sum(\sin\,\omega X_t) \\ \sum(\cos\,\omega X_t) & \sum(\cos^2\omega X_t) & \sum(\cos\omega t\,\sin\omega X_t) \\ \sum(\sin\,\omega X_t) & \sum(\cos\omega X_t\sin\omega)X_t & \sum(\sin^2\omega X_t) \end{pmatrix}^{-1} \begin{pmatrix} \sum(y_t) \\ \sum(\cos\,\omega X_t y_t) \\ \sum(\sin\omega X_t y_t) \end{pmatrix} \tag{8}$$

where β_0, β_j and β_j^{*} are the estimated trigonometric regression model coefficients.

Coefficient of Determination and Adjusted Coefficient of Determination

The Coefficient of determination given in equation 8 will be used to measure the level of variation in the dependent variable explained by the independent variables where SSE is the sum of square of error and SST is the sum of square of total. While the adjusted coefficient of determination given in equation (9) will be used to determine maybe the model has a good fit and has high predictive power where n is the of observation and k is the number of coefficients

$$R^2 \quad = 1 - \frac{SSE}{SST} \tag{9}$$

$$R^2 = 1 - \frac{(\beta_0 \quad \beta_j \quad \beta_j{}^*)\begin{pmatrix} \sum y_t \\ \sum \cos x_t y_t \\ \sum \sin x_t y_t \end{pmatrix} - n\bar{y}^2}{y'y - (\beta_0 \quad \beta_j \quad \beta_j{}^*)\begin{pmatrix} \sum y_t \\ \sum \cos x_t y_t \\ \sum \sin x_t y_t \end{pmatrix}} \tag{10}$$

and

$$\bar{R}^2 = \frac{1}{n-k}[nR^2 - k] \tag{11}$$

Test of Hypothesis

For the individual parameter, the test of hypothesis will be carried out as follows

$$H_0: \widehat{\beta_J} = 0 \; vs \; H_1: \widehat{\beta_J} \neq 0$$

$$t = \frac{\widehat{W_J}}{\sqrt{\sigma_\varepsilon{}^2 C_{jj}}} = \frac{\widehat{W_J}}{S_\varepsilon(\widehat{W_J})} \sim t_{\propto/2}, (n-k-1) \tag{12}$$

where C_{jj} is the diagonal element of $(X'X)^{-1}$ corresponding to $\widehat{\beta_J}$, α is the level of significance and $(n-k-1)$ degree of freedom.

For the joint hypothesis, the steps are as followed

$$H_0: \beta_0 = \beta_J = \beta_J^* = 0$$

$$H_1: \beta_0 = \beta_J = \beta_J^* \neq 0$$

$$F = \frac{SSR/_k}{SSE/_{(n-k-1)}} = \frac{MSR}{MSE} \tag{13}$$

With $(k-1)\, and\, (n-k-1)$ degree of freedom.

Error Term Performance based on Durbin Watson Statistic

If ε_t is the residual associated with the observation at time t, then the test statistic is

$$d = \frac{\sum_{t=2}^{T}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{T}\varepsilon_t^2} \tag{14}$$

Where T is the number of observations. Note that if the sample is lengthy, then this can be linearly mapped to the Pearson correlation of the time-series data with its lags. Since d is approximately equal to $2(1-r)$, where r is the sample autocorrelation of the residuals, $d = 2$ indicates no autocorrelation. The value of d always lies between 0 and 4. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation (Gujarati 2009).

RESULTS AND DISCUSSIONS

This study is used to determine the effects of monthly rainfall and temperature variability on malaria prevalence rate in Ibadan, Oyo State, Nigeria. The monthly malaria prevalence data used in this study were obtained from the Department of Pediatrics of the College of Medicine of the University of Ibadan (COMUI), University College Hospital (UCH), Ibadan, Nigeria from 1996 to 2017. While, the Ibadan monthly climatic variables dataset (rainfall and temperature) was acquired from the International Institute for Tropical Agriculture (IITA) Ibadan, Nigeria; (https://www.iita.org) from 1996 to 2017.

The descriptive statistics results in Table (1) were used to show that the Ibadan monthly mean rainfall is 111.99.mm with a standard deviation of 98.14mm. The maximum rainfall is 402.9mm and the minimum rainfall is 0.00 mm. From Table (1) as well, the Ibadan mean temperature is 32℃ with a standard deviation of 2.41 ℃. The maximum temperature is at 32.2℃ and the minimum temperature is 21.0 ℃. Table 1 was further used to show the average monthly rainfall is 97.1.mm with a standard deviation of 85.74. The maximum rainfall is 318.2 mm and the minimum rainfall is 0.00 mm. The mode and coefficient of variation of Ibadan monthly rainfall, temperature and malaria prevalence series were 0.1mm, 32℃ and 0.47 and 87.63mm, 7.61℃ and 57.6 respectively.

The time plot of Ibadan rainfall, temperature and malaria prevalence proportion are displayed in figures (1)-(3). Figures (1)-(3) showed that Ibadan monthly rainfall, temperature and malaria prevalence proportion exhibited trend, periodic and seasonal variations simultaneously over the period under consideration.

Table1: Descriptive statistics for Ibadan monthly climatic variables and malaria Prevalence proportion

Variable	Mean	StDev	Variance	CoefVar	Sum	Min	Max	Mode	Skewness	Kurtosis
rainfall	111.99	98.14	9630.99	87.63	29565.46	0.00	402.9	0.1	0.64	-0.43
Temp	32	2.41	5.80	7.61	8378.835	26.6	37	32	-0.04	-0.84
Malaria	0.22	0.13	0.016	57.6	57.931	0.02	0.69	0.47	1.22	1.53

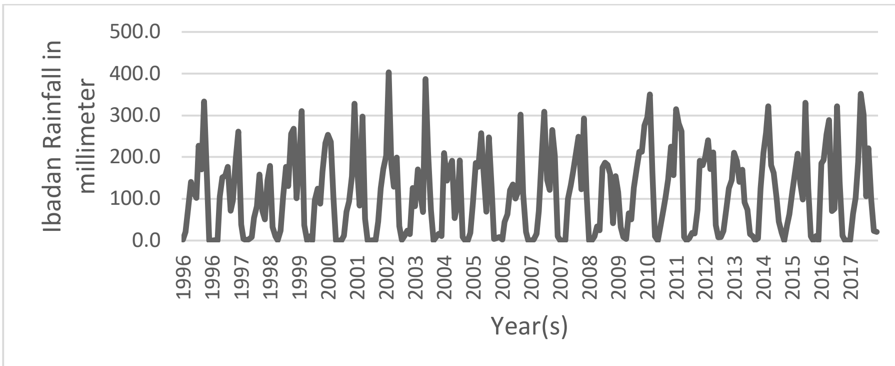

Figure 1. Ibadan rainfall series from 1996 to 2017

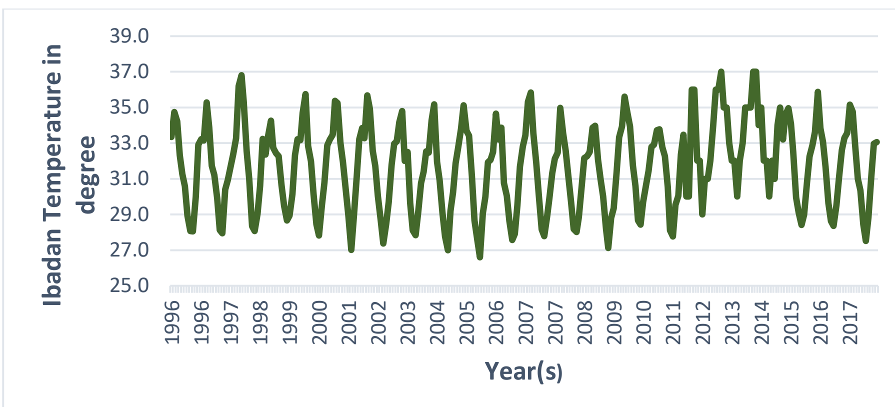

Figure 2. Ibadan temperature series from 1996 to 2017

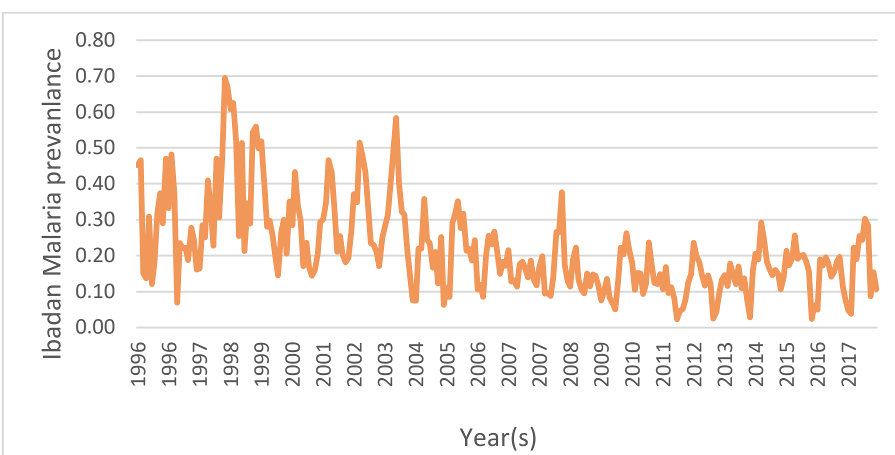

Figure 3. Ibadan malaria prevalence series from 1996 to 2017

In other to determine the effects of Ibadan climatic variability on Ibadan malaria prevalence proportion, the suggested multiple trigonometric regression model that can handle the trend, periodic and seasonal variations in Ibadan rainfall and temperature simultaneously is

$$y_t = \beta_0 + \sum_{j=1}^{2} \beta_j \frac{cos2\pi X_t}{12} + \sum_{j=1}^{2} \beta_j^* \frac{Sin2\pi X_t}{12} + \varepsilon_t \quad (15)$$

where the period is $\frac{\pi}{12}$ $and\ t = 1, 2, \ldots$.

The fitted multiple trigonometric regression model using the OLS estimation method is

$$MALProp_t = 0.2326 - 0.4130 \frac{cos2\pi}{12} rainfall_t - 0.053 \frac{sin2\pi}{12} rainfall_t - 0.258 \frac{cos2\pi}{12} temp_t + 0.200 \frac{sin2\pi}{12} temp_t \quad (16)$$

With $R^2 = 0.6130, Adjusted\ R^2 = 0.8642$ and Durbin Watson Statistics $= 0.6024$

The Durbin Watson statistics values obtained when the model is fitted indicated that the residual terms are not serially correlated. The coefficients of the fitted multiple trigonometric regression model showed that all the coefficients influence Ibadan malaria prevalence proportion. The coefficients of $\frac{cos2\pi}{12} rainfall_t$, $\frac{sin2\pi}{12} rainfall_t$ and $\frac{cos2\pi}{12} temp_t$ indicated that for every unit decrease in Ibadan rainfall and temperature, there might be a decrease in Ibadan malaria prevalence proportion. While the coefficient of $\frac{sin2\pi}{12} temp_t$ indicated that for every unit increase in the Ibadan rainfall and temperature, there might be an increase in Ibadan malaria prevalence proportion. The coefficients of the multiple trigonometric regression model generally indicated that Ibadan climatic variability has a direct influence on the malaria prevalence proportion in Ibadan city. This direct influence can be attributed to climate change with respect to rainfall and temperature currently experiencing globally. The values of coefficient of determination (R^2) revealed that Ibadan city monthly rainfall and temperature jointly explained the variations in Ibadan malaria prevalence proportion up to 61%. The fitted multiple trigonometric regression model has a good fit and high predictive power based on the value of the adjusted coefficient of determination $(\bar{R}^2)$.

In other to determine the significance level of the estimated coefficients, test of hypothesis were carried out. From the results,β_0 is statistically significant, β_j are individually statistically significant, β_j^* are individually statistically significant and all the coefficients are jointly statistically significant.at 0.05 level of significance.

$For\ H_0 : \beta_0 = 0$ vs $H_1 : \beta_0 \neq 0$ using 0.05% level of significance.

$t_{(0.025,263)} = 1.653$

Since all $t_{cal} > t_{tab}$, the null hypothesis is rejected and concluded that β0 is statistically different to zero at 0.05% level of significance.

$For\ H_0 : \beta_j = 0$ vs $H_1 : \beta_j \neq 0$

$t_{(0.025,263)} = 1.653$

Since all $t_{cal} > t_{tab}$, the null hypothesis is rejected and concluded that all β_j are individually statistically different to zero at a 0.05% level of significance

$For\ H_0 : \beta_j^* = 0$ vs $H_1 : \beta_j^* \neq 0$

$t_{(0.025,263)} = 1.653$

Since all $t_{cal} > t_{tab}$, the null hypothesis is rejected and concluded that all β_j^* are individually statistically different to zero at a 0.05% level of significance.

$$H_0 : \beta_i = 0\ vs\ H_1 : \beta_i \neq 0$$

$$F = \frac{MS(Reg)}{MS(RES)} \qquad f_{(0.05,\ 1,\ 259)} = 3.87$$

$$f_{cal} = \frac{MS(Reg)}{MS(RES)} = \frac{0.6445}{0.0152} = 42.40$$

$$f_{cal} = 3.114 > f_{tab} = 3.56$$

Since $f_{cal} > f_{tab}$, we reject H_0 and conclude that all the coefficients are jointly statistically different from zero at a 0.05% level of significance.

CONCLUSION

This study was used to discuss and analyze the effect of rainfall and temperature on Ibadan city malaria prevalence proportion. The time plots were used to establish that Ibadan city rainfall, temperature and malaria prevalence proportion series exhibited secular, periodic and seasonal variations. Multiple Trigonometric regression model that has the capabilities of handling the three variations simultaneously was used. From the results, the residuals of the fitted multiple trigonometric regression model are not serially correlated based on the value of the Durbin Watson Statistics. The coefficients of the fitted model were used to establish that for every unit increase or decreasein Ibadan city rainfall and temperature there might be an increase or decrease in the malaria prevalence proportion of Ibadan city over the years.This may be attributed to climate change and Ibadan city malaria prevalence proportion will likely continue to exhibit secular, cyclical and seasonal variations. The values of coefficient of determination (R^2) revealed that Ibadan city monthly rainfall and temperature jointly explained the variations in Ibadan malaria prevalence proportion up to 61%. The fitted multiple trigonometric regression model as well as a good fit and high predictive power based on the value of the adjusted coefficient of determination ($\bar{R}^2$). The test of hypothesis results showed that β_0 is statistically significant, β_j are individually statistically significant, β_j^* are individually statistically significant and all the coefficients are jointly statistically significant.at 0.05 level of significance.Based on these results, a multiple trigonometric regression model is suitable and adequate for modelling the effect of Ibadan monthly climatic variability on malaria prevalence proportion which can cause a high rate of morbidity and mortality if not curtail or curbed.

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