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Full Length Research Paper

Effect of meteorological variables on malaria incidence in Ogun State, Nigeria

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This study aimed to examine the impact of climatic variation on malaria in Ogun state, Nigeria. A 10-year time-series analysis from 2004 to 2013 was conducted to evaluate the relationship between climatic variables (i.e. rainfall, humidity, minimum and maximum temperature) and malaria cases in Ogun State, Nigeria. Cross-correlation analysis was performed to know the association between meteorological variable at lag 0 to 4 and the number of malaria cases. The ARIMAX model was then used to measure the relationship between them using the significant climatic variables. The results from this study indicated that for every one degree centigrade rise in maximum temperature, the number of malaria cases will decrease between 90.8 and 97.8 percent and a one degree rise in minimum temperature may be related to a decrease in the number of malaria cases between 93.4 and 99.4 percent and one degree rise in minimum temperature may be related to an increase in the number of malaria cases between 0.25 and 6.47 percent. In conclusion, temperature plays a significant role in malaria transmission in Ogun State, Nigeria.

Keywords: Meteorological variables, malaria, Ogun State, ARIMAX, ARIMA, Time series analysis.

INTRODUCTION

Malaria is indeed a great global health problem affecting approximately 106 countries, with half of the world's population at risk (3.4 billion people) (WHO, 2014). The World Health Organization report on malaria in 2013 estimated about 207 million cases of malaria in 2012 (with an uncertainty range of 135 million to 287 million). The estimates for other areas were 174 million cases in Africa, one million cases in the Americas, 10 million cases in Eastern Mediterranean, 200 cases in Europe, 28 million cases in South-East Asia and 2 million cases in the Western Pacific. There was an estimated 627,000 deaths (with an uncertainty range of 473,000 to 789,000) with Africa accounted for 596,000 (91% of total estimated deaths, 86% were in children under 5 years of age), the Americas: 1,000, in Eastern Mediterranean: 15,000 in Europe: 0, Asia: 38,000, South-East Western Pacific: 5,000 (United Against Malaria 2014). It was also estimated that malaria deaths has reduced by 42% globally since 2000 and 54% in African countries. More than 80% of estimated malaria deaths in 2012 occurred in just 17 countries, and 80% of cases occurred in 18 countries, with the Democratic Republic of the Congo and Nigeria together accounting for 40% of the estimated global total. Most deaths occurred among children in Africa. It is estimated that a child dies every minute from malaria and about 460000 African children died before their fifth birthday (WHO, 2014).

Malaria is the third biggest killer of children globally in 2003,

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more than 3000 children died every day from malaria in Africa (UNICEF, 2003). In fact a child somewhere in the world dies every minute of malaria and African children are killed every 30 seconds. It is also estimated that 86% of total malaria deaths in the world were in children under five years of age (UNICEF, 2013). Figure 1 shows the different ways in which malaria kills children. There are three principal mechanisms; the first is low birth weight due to infection in pregnant women.This is the major risk factor for death during the first month of life. Second, an acute infection which may be presented as seizures and coma (cerebral malaria), may kill a child directly and quickly. The third is repeated malaria infection which could progress to severe malaria and substantially increases the risk of death (The Africa Malaria Report, 2003).

Malaria infection during pregnancy is a major public health problem in tropical and subtropical regions throughout the world. In endemic areas such as Africa, pregnant women are the main risk group among the adult population for malaria. Figure 2 shows the mechanisms of malaria infection in pregnant women. When compared to non-pregnant women, pregnant women are 3 times more likely to suffer from severe disease and have a mortality rate from severe disease that approaches 50% (Monif, et al. 2004). The highest rate of malaria infection appears to be in the second trimester. The highest risk for infection and morbidity is in primigravidas, adolescents, and those infected with HIV (Desai et al. 2007). It is assumed that the majority of malaria infections during pregnancy results from two main factors: the immunocompromised state of pregnancy and placental sequestration of infected erythrocytes. Adults who live in malaria endemic regions acquire some immunity to malaria infection as a result of immunoglobulin production during prior infections in childhood. This immunity diminishes significantly in pregnancy, particularly in primigravidas.

A study conducted among 300 women in rural Ghana found a higher rate of anemia, clinical malaria, and placental burden of infection among primigravidas compared with multigravidas (Ofori, et al, 2009). Splenic sequestration of malaria infected erythrocytes leads to folic acid deficiency and microcytic anemia in adults. In pregnant women, additional sequestration of malaria-infected erythrocytes occurs in the placenta. Pregnant women therefore suffer disproportionately from severe anemia as a result of infection. Interestingly, the greatest degree of placental infestation is seen in women who have the highest level of immunity, leading to milder maternal symptoms but a disproportionate increase in fetal complications (Monif, et, al 2004). According to the Nigeria Malaria Control Program Strategic Plan 2009-2013, about 60% of outpatient visits and 30% of hospitalizations in Nigeria are due to malaria. Also, it accounted for about 11% of maternal mortality and 10% of low birth weight annually.

The effect of meteorological variables and malaria transmission has been extensively studied among different population around the world, few studies in tropical areas in Nigeria and non to the best of our knowledge in Ogun state, Nigeria. Environmental conditions generally affect the survival and behaviour of anopheles, but some species are better adapted to extreme conditions than others. Altitude is also an important factor in malaria transmission and it is generally stated that transmission does not normally occur above 1,800 m (Bodker, et, al 2003). Microclimatic conditions, particularly humidity, affect the entry of mosquitoes into houses. The outdoor biting activity is much more marked during the dry season than during the rains, the reverse may be true in extremely dry situations. Temperature can affect the transmission of malaria parasites in various ways and an increase in temperature can results in shortened sporogonic period of Plasmodium parasites within the vector up to about 30 degree Celsius and a mean daily temperatures above 30 degree Celsius will have a negative impact on the survival of the vector (Craig, et al, 1990). Oluleye and Akinbobola (2010) also study the role of climatic parameters and the severity of some common diseases such as malaria and pneumonia in Lagos, Nigeria. Temperature and malaria were found to be positively correlated in the months of February and December and negatively correlated in November.

The purpose of this study was to examine the effects of climatic factors on the transmission of malaria in Ogun State, Nigeria using an autoregressive integrated moving average with exogenous variable (ARIMAX) models.

Study Location

Ogun state is located at the south-western part of Nigeria. The population as of the 2011 Census was 4,397,604. There were 2,186,301 males and 2,211,303 females (Ogun State Government, 2014). The land area of the state is about 6,335.7 square miles (16,409 square kilometers). Ogun State is located in a moderately hot, humid tropical climatic zone of southwest part of Nigeria. There are two distinct seasons in the state namely, the rainy season which from March/April to October/November and the dry season which lasts for the rest of the year, October/November till March/April. The temperature is relatively high during the dry season with a mean temperature of around 30°C. The harmattan, brought in the northeasterly winds from December February, has ameliorating effects on the dry season high temperatures. Low temperatures are experienced during the rains, especially between July and August when the temperatures could be as low as 24°C. The distribution of rainfall varies from about 1000 mm in the western part to about 2000 mm in the eastern part, especially Ijebu and Ogun Waterside local government areas (Online Nigeria, 2014).

MATERIALS AND METHODS

We used historical monthly data for both malaria cases and climatic variables for Ogun State from 2004-2013.

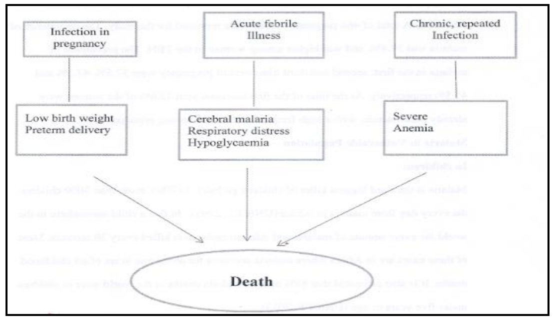

Figure 1. Different ways in which malaria kills children.
Source: The African Malaria Report, 2013.

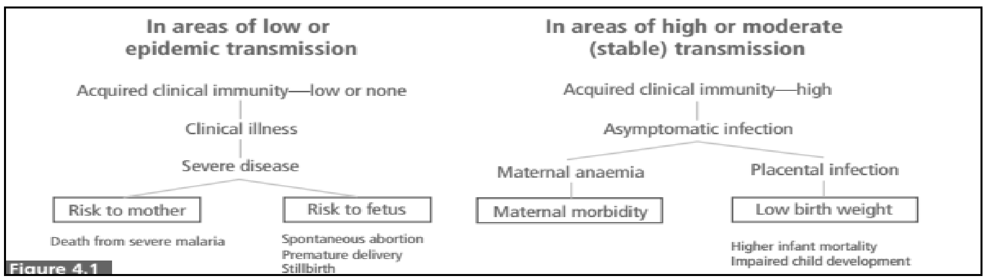

Figure 2. Malaria During Pregnancy.
Source, The African Malaria Report, 2013.

Malaria data were abstracted from the monthly health directorate data from 2004-2013 for Ogun State. This health malaria surveillance database is maintained by the Ogun State Ministry of Health. The malaria data were received from the primary, secondary and tertiary clinics and hospital from all the 20 local government of the state. This data consist of malaria cases and deaths for all people less than 5 years, 5-14 years and greater than 15 years and malaria cases and deaths for pregnant women. Cases were classified based on severity; 1) Uncomplicated cases; which is the malaria attack that lasts for 6-10 hours and is considered an outpatient case, 2) Severe cases, in which infections are complicated by serious organ failures or abnormalities in the patient's blood or metabolism and are inpatients. After receiving the data from the hospitals and clinics, the data entry manager calculated the cases by clinic and entered them into the malaria database using the Microsoft Excel software. Reports were also generated using this software. This report is computed and sent to the national malaria surveillance system in Abuja, Nigeria. The meteorological data from 2004-2013 was collected from the Nigeria Meteorological Agency and consisted of average monthly rainfall, monthly mean relative humidity, monthly mean minimum and mean maximum temperature. This data was received from the national office from each weather station across the country. The data was used to generate a report in the national climatic database using Microsoft Excel. In Ogun state, the two weather stations are located in Abeokuta the state capital and Ijebu Ode another major city in the state. These cities are about 89km (55 miles) apart from each other. The maximum temperature is the average of the overall maximum temperatures measured on each day (which is usually in the afternoon). For example for January, the maximum temperatures for each day divided by 31). The same procedures used for maximum temperature were employed to calculate monthly averages for the minimum temperature and average humidity. The monthly rainfall is different because some days may have no rainfall (zero rainfall), therefore, rainfall for the month was noted as the total rainfall for the month rather than the average, (e.g. if the January value is 200, this is the total rainfall for January 1 to January 31 of that year).

Data Management

The data collected from the malaria program database, malaria cases, deaths and severity of malaria cases was compiled monthly from 2004-2013. These data were entered into a Microsoft Excel spreadsheet for cleaning. During cleaning, some cases were found to be missing for year 2009 (July-December); while some did not have sufficient records for further analyses. For the missing values the cubic spline interpolation method was used to interpolate and assign the missing values. The cubic spline interpolation is a common numerical curve fitting strategy that fits a "smooth curve" to the known data, using cross-validation between each pair of adjacent points to set the degree of smoothing and estimate the missing observation by the value of the spline. Also, due to inconsistencies in reporting, some years did not have the same variables as the other. For example 2007, 2008 and 2009 only reported malaria severity while in 2004; ages were only reported while the severity was missing. In order to make the best use of the dataset and to be able to reach an accurate result as possible, variables with inconsistent records were removed from the final analysis. Overall, the final data includes the monthly malaria cases from 2004-2013 for all ages.

Statistical Analysis

The analysis for this study included descriptive and time series analysis (ARIMA, ARIMAX and cross correlation).

ARIMA Model

The ARIMA model involves estimating a series of parameters to account for the dynamics of a time series. This includes the trends, and the autoregressive and moving average processes. The autoregressive and moving average parameters that included differencing in the formation of the model was introduced by Box and Jenkin (1976). This model includes three types of orders: There are (p) AR parameters, (I) Integration parameters and (q) MA parameters.The ARIMA (Autoregressive integrated moving average) for this study was first applied to the malaria series without including the independent variables. Visual observation of the series shows that the mean and variance of the series is not constant, therefore a logarithmic transformation was applied to the malaria series to assure the normality and homogeneity of the variance of the residuals. The best ARMA process was then selected for the trend of the malaria series using an Akaike Information Criterion (AIC) method of selection. This identifies the best order of a stationary and invertible ARMA process.

ARIMAX Model

The ARIMAX model is an extension of the ARIMA model. This model includes predictor or exogenous variables. An ARIMAX model was used to evaluate the relationship between the monthly weather variables and the monthly malaria incidence from 2004 to 2013 considering rainfall, temperature and humidity. The SARIMA (Seasonal Autoregressive integrated moving average) type of ARIMAX model was used in this study. The model required the use of differencing and transformations to stabilize the time series data (Shumway and Stoffer, 2000). The multiplicative type of SARIMA (p,d,q) (P,D,Q) was utilized for independent variables. The multiplicative ARIMAX method is when a pattern of time series repeats seasonally over time. The (p,d,q) is the same as the ARIMA model while the seasonal parameters are seasonal autoregressive (P), seasonal differencing (D) and seasonal moving average (Q), (Zhang et al, 2010). The logarithmic transformation that was applied to the malaria series in the ARIMA model was carried forth to the ARIMAX model. Since the weather variables showed different trend in their series, different transformation and differentiation was applied to each series. Temperature (minimum and maximum) was differenced at lag 12, while humidity and rainfall was log transformed. This was done to achieve stationarity to ensure normality and homogeneity of variance of the residuals. In order to examine the association between the weather series and malaria series, cross correlation analysis was performed. Each of the input series (that is the weather variables) at lag of zero to four months was included in the initial ARIMAX model of the monthly malaria incidence to determine the potential weather predictors of malaria cases. However, only those input variables that were significantly associated with the monthly malaria incidence with a p-value of less than 0.05 were singled out and retained in the final multivariate ARIMAX model. The best fit seasonal ARMA process was selected by using the Akaike Information Criterion (AIC) model, which measures how well the model fits the series and the lowest AIC was considered the best model. The maximum likelihood estimate was used to provide an estimate for the model parameters. The final ARIMAX (regression model with input series) which includes only the significant weather variables as the independent factors and the malaria series as the dependent factors were used.All significant input (weather) series at their respective differences and transformation were cross correlated with the logarithmic transformation of the malaria cases between their residue series and also fitted to their respective seasonal ARMA processes. Akaike Information Criterion (AIC) model was used to select the best fit for both the malaria cases and the input series. All the analyses were performed using SAS® Version 9.3 (SAS Institute Inc, Cary, NC).

RESULTS

There were 1,937,601 malaria cases from January 2004 to December 2013 in Ogun state, Nigeria. With an average of 16,147 cases per month, the cases ranged from 7,153 in January 2005 to maximum case of 30,459 in February, 2012. Some of the lowest cases were recorded in February 2004 (8,633 cases), April, 2004 (8,257cases) January, 2005 (7,153 cases), February, 2005 (8,191 cases) and April, 2005 (8,179 cases). The highest cases were recorded in February, 2012 (30,459 cases), June, 2012 (28,754 cases), July, 2012 (27,255 cases), August, 2012(26,388 cases) and November, 2012 (26,959 cases). This high rate of cases coincides with the rainy season in Ogun state which is between March/April to October/November.

Figure 3 shows the variation of monthly cases from January 2004 to December 2013. The lowest number of cases occurred in January 2005 (7,153) with the highest number of cases in February 2012 (30,459).

Meteorological Variables

Maximum Temperature

The average maximum temperature was 32.35 degree centigrade. The maximum temperaure ranged from 28.3 in July, 2013 to 36.8 degrees centigrade in February, 2010.
Figure 4 shows the variation of maximum temperature between January 2004 and December 2013.

Minimum Temperature

The average minimum temperature wis 23.3 degree centigrade. The minimum temperaure ranges from18.1 in January, 2008 to 26.2 degrees centigrades in April, 2010.
Figure 5 shows the variation of minimum temperature between January 2004 and December 2013.

Rainfall

The average rainfall was 128.9mm. The rainfall ranged from 0mm (Zero) in January, 2008, December, 2010,January, 2011, January, 2012 and December, 2012 during the dry season to 415.6mm in June, 20009 in the middle of the rainy season. The highest rainfall was recorded in September 2010 (341.3mm), June 2007 (372.9mm), July 2008 (387mm), July 2011 (414.4mm), and June 2009 (415.6mm). Figure 6 shows the variation of the monthly rainfallin Ogun state between January 2004 and December 2013.

Relative Humidity

The average relative humidity was 78.3 percent. The relative humidity ranges from 52% in January, 2007 to 90% inAugust, 2007. Some of the lowest humidity were recorded in the months and years of January, 2007 (52%), January, 2009 (52.5%), February, 2007 (52.5%), February, 2013 (53.5%) and February, 2008 (54.5%) and the highest relative humidity were recorded in the months and years of September, 2005 (88.5%), October, 2009 (88.5%), July, 2007 (89%), August, 2004 (89.5%) and August, 2007 (90%).Figure 7 shows the variation of the monthly relative humidity in Ogun state between January 2004 and December 2013.

ARIMAX Model

The association between malaria incidence and weather variables was performed by first analyzing the correlation between the malaria series and the weather input series at lags 0 to 4 which includes a time trend. After the correlation of the series was done to eliminate those series that are not significant at a p-value less than 0.05, the significant meteorological variables were then included in the final ARIMAX model. Sixteen different models were built to know the association between malaria cases and meteorological variables (at lag 0 to 4). Each model include the time trend of the log-transformed malaria cases with the input variables rainfall log-transformed plus 1 and differenced at lag 12 and the minimum, maximum and humidity differenced at lag 12. Overall, minimum temperature at lag 1 and 3 and maximum temperature at lag 1 and 4 shows a significant relationship between malaria cases and this was the only variables included in the final model.

Model 1: Malaria Cases = Rainfall
Model 2: Malaria Cases = Humidity
Model 3: Malaria Cases = Minimum Temperature
Model 4: Malaria Cases = Maximum Temperature
Model 5: Malaria cases = Rainfall + Humidity + Minimum Temperature
Model 6: Malaria cases = Rainfall + Humidity + Maximum Temperature
Model 7: Malaria cases = Rainfall + Maximum Temperature
Model 8: Malaria cases = Rainfall + Minimum Temperature
Model 9: Malaria cases = Rainfall + Minimum Temperature + Maximum
Temperature
Model 10: Malaria cases = Rainfall + Humidity
Model 11: Malaria cases = Humidity + Maximum Temperature + Minimum Temperature
Model 12: Malaria cases = Humidity + Maximum Temperature
Model 13: Malaria cases = Humidity + Minimum Temperature
Model 14: Malaria cases = Minimum Temperature + Maximum Temperature
Model 15: Malaria cases = Rainfall + Humidity + Minimum Temperature + Maximum Temperature
Model 16: Malaria cases = Rainfall + Humidity + Minimum Temperature + Maximum Temperature (Multiple Linear regression)
Model 17 (Final Model): Malaria cases = Maximum Temperature (lag 1 and 4) + Minimum Temperature (lag 1 and 3). (Significant variables).

The following models are presented for the significant predictors of malaria cases from the ARIMAX procedures.

Model 4: Malaria Cases = Maximum Temperature

Table 1 presents the maximum likelihood estimates for the model. This model included the malaria cases as the dependent variable and maximum temperature as the independent variable. In this model, the log-transformed

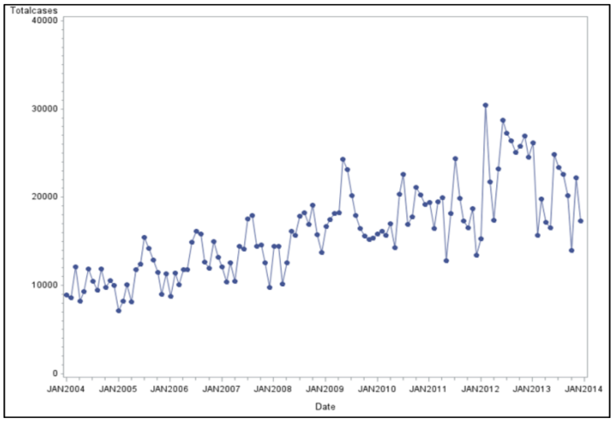

Figure 3. Monthly malaria cases between January 2004 and December 2013.

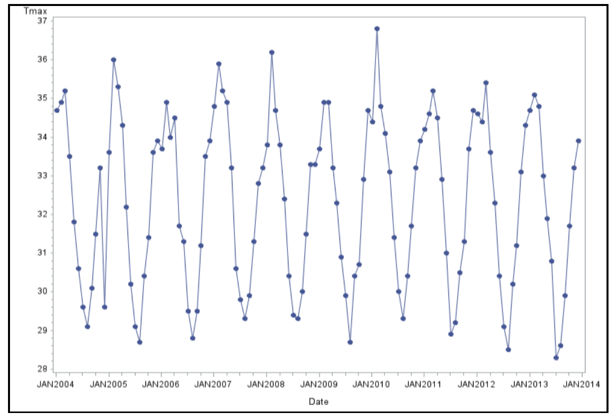

Figure 4. Monthly maximum temperature between January 2004 and December 2013.

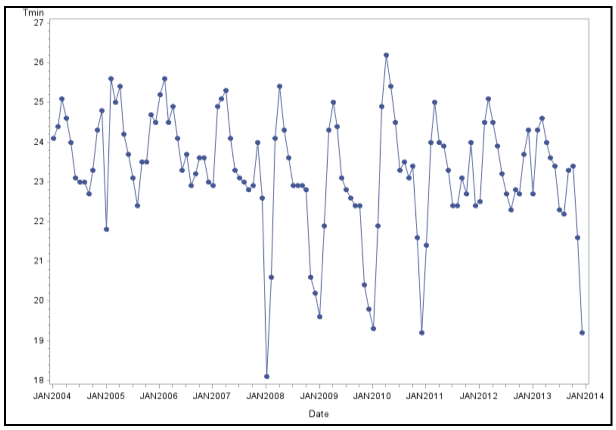

Figure 3. Monthly minimum temperature between January 2004 and December 2013.

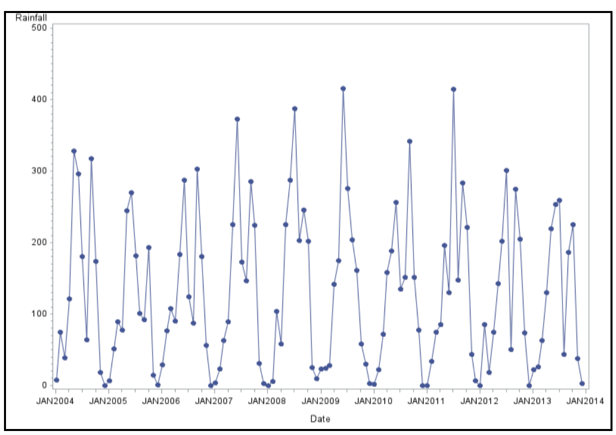

Figure 6. Monthly Rainfall in mm between January 2004 and December 2013.

malaria cases were cross-correlated with the maximum temperature differenced at lag 12. Next a transfer function of maximum temperature for lag 0, 1,2,3 and 4 was fit with the model with no structure on the noise term.

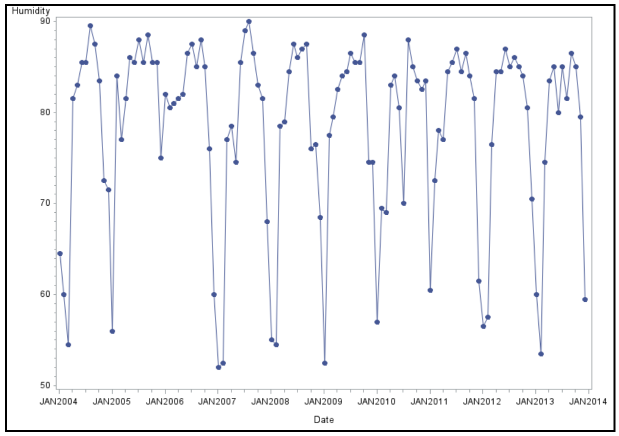

Figure 4. Monthly relative humidity between January 2004 and December 2013.

Parameter	Estimate	Standard Error	t Value	Approx Pr> |t|	Lag	Variable	Shift
MU	9.29711	0.07388	125.84	<.0001	0	logy	0
AR1,1	0.42458	0.09365	4.53	<.0001	1	logy	0
NUM1	0.0060706	0.0009862	6.16	<.0001	0	time	0
NUM2	0.0045276	0.02219	0.20	0.8384	0	Tmax	0
NUM1,1	0.05257	0.02280	2.31	**0.0211**	1	Tmax	0
NUM1,2	0.0074810	0.02260	0.33	0.7406	2	Tmax	0
NUM1,3	0.0028116	0.02281	0.12	0.9019	3	Tmax	0
NUM1,4	0.02925	0.02170	1.35	0.1777	4	Tmax	0

Table 1. Maximum Likelihood Estimation of an AR (1) Model for Model 4.

Residuals from this model were analysed. After analysing the residual, AR (1) model was found to be the best noise term for the model and was added to the full model.The result for this model shows that there is no correlation between maximum temperature and malaria cases at lag 0 (0.4600), lag2 (0.7631), lag3 (0.1095) and lag4 (0.1196), since the p-value is greater than 0.05 it is not statistically significant however there is a relationship at lag1 (0.0211) and it is statistically significant.

Model 9: **Malaria cases = Rainfall + Minimum Temperature + Maximum Temperature**

Table 2 presents the maximum likelihood estimates for the model. This model include the malaria cases as the dependent variable and maximum temperature, minimum temperature and rainfall as the independent variable. In this model, the log-transformed malaria cases was cross-correlated with the maximum temperature and minimum temperatureand at lag 12 and log-transformed rainfalldifferenced at lag 12 . Next a transfer function of all the independent variables for lag 0, 1,2,3 and 4 was fit with the model with no structure on the noise term. Then the residuals from this model were analysed. After analysing the residual, MA (1) Model model was found to be the best noise term for the model and was added to the full model.

The result for this model shows that there is no statistically significant correlation between malaria cases and maximum temperature and rainfall at lag 0 , 2, 3,4 but there is a positive correlation between malaria cases and maximum temperature at lag of one month (p-value=0.0130) and a negative correlation of malaria cases and minimum temperature at lag 1 (p-value=0.0276).

Model 11: Malaria cases = Humidity+ Minimum Temperature + Maximum Temperature

Table 3 presents the maximum likelihood estimates for this model. This model include the malaria cases as the dependent variable and maximum temperature, minimum temperature and humidity as the independent variable. In this model, the log-transformed malaria cases was cross-correlated with the maximum temperature, humidity and minimum temperature differenced at lag 12. Next a transfer function for all the independent variables for lag 0, 1,2,3 and 4 was fitted with the model with no structure

Parameter	Estimate	Standard Error	t Value	ApproxPr> |t|	Lag	Variable	Shift
MU	9.32349	0.06412	145.41	<.0001	0	logy	0
MA1,1	-0.82096	0.10219	-8.03	<.0001	1	logy	0
AR1,1	-0.23896	0.15883	-1.50	0.1325	1	logy	0
NUM1	0.0057352	0.0008532	6.72	<.0001	0	time	0
NUM2	0.0029529	0.02356	0.13	0.9003	0	Tmax	0
NUM1,1	0.06283	0.02529	2.48	**0.0130**	1	Tmax	0
NUM1,2	0.01769	0.02492	0.71	0.4778	2	Tmax	0
NUM1,3	0.02064	0.02524	0.82	0.4133	3	Tmax	0
NUM1,4	0.02797	0.02279	1.23	0.2197	4	Tmax	0
NUM3	-0.0067238	0.02035	-0.33	0.7411	0	lograinfallplus	0
NUM1,1	-0.0023873	0.02362	-0.10	0.9195	1	lograinfallplus	0
NUM1,2	-0.02574	0.02430	-1.06	0.2895	2	lograinfallplus	0
NUM1,3	0.02105	0.02463	0.85	0.3927	3	lograinfallplus	0
NUM1,4	0.0042162	0.02083	0.20	0.8396	4	lograinfallplus	0
NUM4	0.0021144	0.01547	0.14	0.8913	0	Tmin	0
NUM1,1	-0.03783	0.01717	-2.20	**0.0276**	1	Tmin	0
NUM1,2	0.0006926	0.01848	0.04	0.9701	2	Tmin	0
NUM1,3	-0.03174	0.01837	-1.73	0.0840	3	Tmin	0
NUM1,4	0.0036355	0.01688	0.22	0.8295	4	Tmin	0

Table 2. Maximum Likelihood Estimation of an MA (1) Model for Model 9.

Parameter	Estimate	Standard Error	t Value	Approx Pr> |t|	Lag	Variable	Shift
MU	9.34203	0.07046	132.58	<.0001	0	logy	0
MA1,1	-0.54131	0.09962	-5.43	<.0001	1	logy	0
NUM1	0.0054901	0.0009396	5.84	<.0001	0	time	0
NUM2	-0.0046515	0.02493	-0.19	0.8520	0	Tmax	0
NUM1,1	0.06482	0.02623	2.47	**0.0135**	1	Tmax	0
NUM1,2	0.02238	0.02538	0.88	0.3779	2	Tmax	0
NUM1,3	0.02123	0.02628	0.81	0.4191	3	Tmax	0
NUM1,4	0.04863	0.02428	2.00	**0.0452**	4	Tmax	0
NUM3	0.0015801	0.0025732	0.61	0.5392	0	Humidity	0
NUM1,1	-0.0011894	0.0025853	-0.46	0.6455	1	Humidity	0
NUM1,2	0.0032297	0.0024918	1.30	0.1949	2	Humidity	0
NUM1,3	0.0017471	0.0024279	0.72	0.4718	3	Humidity	0
NUM1,4	0.0007893	0.0023221	0.34	0.7339	4	Humidity	0
NUM4	0.0021941	0.01653	0.13	0.8944	0	Tmin	0
NUM1,1	-0.03001	0.01747	-1.72	0.0858	1	Tmin	0
NUM1,2	-0.01316	0.01782	-0.74	0.4602	2	Tmin	0
NUM1,3	-0.04074	0.01826	-2.23	**0.0257**	3	Tmin	0
NUM1,4	0.01744	0.01741	1.00	0.3163	4	Tmin	0

Table 3. Maximum Likelihood Estimation of an MA (1) Model for Model 11.

on the noise term. Then the residuals from this model were analysed. After analysing the residual, MA (1) Model model was found to be the best noise term for the model and was added to the full model.

The result for this model shows that there is no statistically significant correlation between malaria cases and humidity at lag 0 , 1, 2, 3,4, but there is a positve correlation between malaria cases and maximum temperature at lag of one and four month (p-value=0.0135 and 0.0452 respectively) and a negative correlation of malaria cases and minimum temperature at lag 3 (p-value=0.0257).

Model 14: Malaria cases = Maximum Temperature + Minimum Temperature

Table 4 presents the maximum likelihood estimates for the model. This model include the malaria cases as the

Parameter	Estimate	Standard Error	t Value	Approx Pr> |t|	Lag	Variable	Shift
MU	9.32032	0.06692	139.28	<.0001	0	logy	0
MA1,1	-0.54865	0.09537	-5.75	<.0001	1	logy	0
NUM1	0.0057701	0.0008907	6.48	<.0001	0	time	0
NUM2	0.0018374	0.01561	0.12	0.9063	0	Tmin	0
NUM1,1	-0.03313	0.01667	-1.99	**0.0469**	1	Tmin	0
NUM1,2	-0.0070951	0.01693	-0.42	0.6751	2	Tmin	0
NUM1,3	-0.03632	0.01685	-2.16	**0.0311**	3	Tmin	0
NUM1,4	0.01941	0.01609	1.21	0.2275	4	Tmin	0
NUM3	-0.0022605	0.02281	-0.10	0.9211	0	Tmax	0
NUM1,1	0.06030	0.02405	2.51	**0.0122**	1	Tmax	0
NUM1,2	0.01444	0.02424	0.60	0.5514	2	Tmax	0
NUM1,3	0.01515	0.02468	0.61	0.5393	3	Tmax	0
NUM1,4	0.03872	0.02243	1.73	0.0843	4	Tmax	0

Table 4. Maximum Likelihood Estimation of an MA (1) Model for Model 14.

dependent variable and maximum temperature, minimum temperature as the independent variable. In this model, the log-transformed malaria cases was cross-correlated with the maximum temperature and minimum temperature differenced at lag 12. Next a transfer function for all the independent variables for lag 0, 1,2,3 and 4 was fitted with the model with no structure on the noise term. Then the residuals from this model were analysed. After analysing the residual, MA (1) Model model was found to be the best noise term for the model and was added to the full model.

The result for this model shows that there is a positve correlation between malaria cases and maximum temperature at lag of one (p-value=0.0122) and a negative correlation between malaria cases and minimum temperature at lag 1 and 3 (p-value=0.0469 and0.0311).

Model 17 (FINAL MODEL): Time Series regression for all the independent significant variables

The maximum likelihood estimates for the model are presented in Table 5. This model includes only the significant lag independent variables (minimum temperature at lag 1 and 3 and maximum temperature at lag 1 and 4) from the cross-correlation analysis with the ARMA error for each of the variables.

For this model the independent variables that is the differenced minimum temperature and maximum temperature was first modeled with a univariate ARMA model. Next, the dependent variable (malaria cases) is cross-correlated with the independent variables with the ARMA errors.Next, a transfer function model with minimum temperature at lag 1 and 3 and maximum temperature at lag 1 and 4 is fitted with no structure on the noise term. The residuals from this model were analysed; then, the full model, transfer function and noise, was fitted to the data.

The model indicates that the number of cases were a 1-order moving average (MA1). The result for this model shows that there is a correlation between malaria cases and maximum temperature at lag 1 and minimum temperature at lag 1 and 3. For maximum temperature, the model suggest that in Ogun State, for every one degree centigrade increase in the differenced maximum temperature at lag 12, the number of malaria cases will decreased by an estimate (exponential(-0.05973) = 0.9420) 94.2 percent with a confidence interval between (exponential(-0.022)=0.9782) and exponential (-0.097)=0.907556) that is 90.8 and 97.8 percent at one-month lag time. For minimum temperature, the model suggest that in Ogun State,for every one degree centigrade increase in the differenced minimum temperature at lag 12, the number of malaria cases will decrease an estimate (exponential(-0.03712) = 0.9636) 96.4 percent with a confidence interval between (exponential(-0.0061)=0.9939) and exponential (-0.068)=0.9343) that is 93.4 and 99.4 percent at three -month lag time and increase by an estimate of (exponential(0.03258) = 1.033) 3.3 percent with a confidence interval between (exponential (0.0025)=1.0025) and exponential (0.0627)=1.0647) that is 0.25 and 6.47 percent at one -month lag time.

DISCUSSION AND CONCLUSION

This study examined the relationship between climatic conditions (temperature, rainfall and relative humidity) and the incidence of malaria using historical data from 2004 to 2013. An ARIMAX model was utilized to analysis the association between the meteorological variables and malaria cases using only the significant meteorological variables which is the minimum and maximum temperature. For maximum temperature, the model suggest that in Ogun State, for every one degree centigrade increase in the differenced maximum temperature at lag 12, the number of malaria cases will decrease by an estimate (exponential (-0.05973) = 0.9420) 94.2 percent with a confidence interval between

Parameter	Estimate	Standard Error	t Value	Approx Pr> |t|	Lag	Variable 95% CI	Shift
MU	9.31509	0.06174	150.86	<.0001	0	Logy	0
MA1,1	-0.54554	0.09139	-5.97	<.0001	1	Logy	0
NUM1	0.0058460	0.0008247	7.09	<.0001	0	Time	0
NUM2	0.03258	0.01535	2.12	**0.0338**	0	Tmin **(0.0025,0.0627)**	1
NUM1,1	-0.03712	0.01581	-2.35	**0.0189**	2	Tmin **(-0.0061,-0.068)**	1
NUM3	-0.05973	0.01916	-3.12	**0.0018**	0	Tmax **(-0.022,-0.097)**	1
NUM1,1	0.03679	0.01907	1.93	0.0537	3	Tmax	1

Table 5. Maximum Likelihood Estimation for Model 17.

(exponential (-0.022) =0.9782) and exponential (-0.097) =0.907556) that is 90.8 and 97.8 percent at one-month lag time. For minimum temperature, the model suggest that in Ogun State, for every one degree centigrade increase in the differenced minimum temperature at lag 12, the number of malaria cases will decrease an estimate (exponential(-0.03712) = 0.9636) 96.4 percent with a confidence interval between (exponential(-0.0061)=0.9939) and exponential (-0.068)=0.9343) that is 93.4 and 99.4 percent at three -month lag time and increase by an estimate of (exponential(0.03258) = 1.033) 3.3 percent with a confidence interval between (exponential (0.0025)=1.0025) and exponential (0.0627)=1.0647) that is 0.25 and 6.47 percent at one -month lag time. Maximum and minimum temperatures are predicting factors for malaria in Ogun State. This is in support of the hypothesis that meteorological variables will have a significant effect on malaria incidence in Ogun State and this is also supported by different literatures which includes Akinbobola and Omotosho in 2013, Klutse, et al, in 2014 and Zhang in 2010.This study was able to find a relationship between maximum and minimum temperature but could not find any association between rainfall, humidity and malaria incidence which has been reported from previous studies. A study conducted by Gupta (1996) in a large state of Rajasthan in India shows that there is a positive relationship between the amount and duration of rainfall and malaria incidence. Small, Goetz and Hay (2003) also supported this finding that rainfall rather than temperature is associated with malaria transmission in Africa. However, a study by Abeku et al (2003) in Ethiopia reported an inverse relationship between rainfall and malaria incidence.The findings from this study show consistency with other studies conducted in Africa and other parts of the world. Akinbobola and Omotosho (2013) conducted a study to know the relationship between climatic variable and malaria incidence in two different cities in Nigeria and reported a negative relationship between malaria incidence and maximum temperature at lag one month and no lag in one city and a positive relationship between malaria incidence and minimum temperature in another city. A strong negative relationship between maximum temperature and malaria transmission was detected in two communities in two ecological zones in Ghana (Klutse, et al, 2014). Also, a study in Shandong province in China suggested a strong positive relationship between both maximum and minimum temperature and malaria transmission (Zhang, 2010).

Strengths and Limitations

The study has a number of limitations. Since the data used for this study was a secondary data, this study is prone to some of the limitations associated with secondary data usage which includes data quality, data accuracy and less control on the data since the data was collected for different purpose. Some of the cases for some months were missing and in order to minimize the impact of this on the results, a cubic spline interpolation method was used to replace the missing cases. The unavailability of daily or weekly data for malaria cases and meteorological variables rather than a monthly report would have increase the accuracy of the analysis, particularly when climatic conditions were considered over a monthly period. Lastly, socio-economic factors and potential confounding factors such as malaria intervention program instituted by the state which could affect the transmission of malaria were not included in the analysis due to unavailability of data.

The major strength of this study was that both ARIMA and ARIMAX model of time series analysis were used to evaluate the relationship between incidence of malaria and meteorological variables.

RECOMMENDATION

This study looked at the relationship between the monthly malaria cases and monthly climatic conditions. Studies that analyze the daily or weekly cases in relations to its daily and weekly climatic conditions with the inclusion of some confounding and socio economic factors are recommended. Also, studies analyzing malaria cases in smaller geographical areas in respect to the climatic conditions of the areas instead of looking at a larger area like Ogun States are recommended. This will provide more precise and reliable results.

CONCLUSION

This study demonstrates that there is a relationship between climatic conditions and malaria cases in Ogun State, Nigeria. Maximum and minimum temperatures are predictors for malaria incidence. The maximum temperature shows an inverse relationship between malaria incidences. While minimum temperature shows both inverse and positive relationship with malaria cases in Ogun State. The result from this study also supports some literatures that shows a relationship between climatic conditions and malaria incidence.

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