Data Analytics of Climatic Factor Influence on the Impact of Malaria Incidence

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***Abstract*—Predicting association between the malaria risk and its climatic predictors provides individuals and public health officials with prior knowledge for effective prevention and control measures. This paper presents an integrated analysis of a total of 2,148 confirmed cases of malaria incidence for Aboh Mbaise General Hospital, together with the satellite meteorological data downloaded from National Centre for Environmental Prediction (NCEP). By pre-whitening the climatic data sets and analysing their cross-correlation with the malaria incidence, we find that temperature and precipitation have negligible lagged effects on the malaria occurrence in the study area. A further analysis reveals that relative humidity shows significant association (P-value < 0.05) with the malaria incidence. However, regression model with autoregressive error structure AR(1) is then used to establish the relationship between the malaria incidence and relative humidity time series. The findings look to confirm the significant contribution of relative humidity to the malaria incidence in the study area due to its high humidity characteristics (about 74% average relative humidity) occurring mostly during the wet season.**

I. Introduction

Malaria is one of the most devastating infectious diseases that affect larger proportion of the World population, whereby its gravity of prevalence clustered around tropical and subtropical regions. Despite the continuing effort by the World Health Organisation (WHO) and other Health donor agencies in combating malaria transmission, the impact of annual morbidity remains significant with gradual mortality decrease [1]. About 20% of pregnant women live in rural areas experiencing parasite infection [2], [3] and children of age less than five are among the most vulnerable cohort of the population as reported in [4]. The devastation impact of malaria accounts for huge burden in the economy with resultant economic lost, school absenteeism and poor output in agricultural productivity especially where farming becomes a primary source of livelihood.

Inspite of technological advancement in modern diagnostics facilities, drugs for treatment and treated bed-net for a preventive measure, malaria remains a public health problem in developing countries including Nigeria. The peak period of malaria transmission in Nigeria occurs mostly during the rainy season and often coincides with the cultivation months [5], [6], which naturally imposes an adverse effect on agricultural production.

Previous works [1], [8]–[11] revealed that malaria transmission has a link to climatic factors such as rainfall, temperature and humidity. The rainfall and temperature influence to the life cycle of the $Anopheles$ mosquito and the $Plasmodium$ spp [1], and there exists a lagged correlation between the malaria incidence and precipitation [12], [13]. Malaria incidence mostly occurs during the rainy season [12] because of the increase in the number of mosquito breeding sites.

Despite an apparent link between the aforementioned climatic factors and malaria transmission, their exact contributions to the actual malaria incidence have not been fully understood. Previous works [5], [17] used a time series analysis to determine the trends in the reported malaria cases and deaths considering the incidence data in Ethiopia and Gabon. References [3], [15], [16] used meteorological and malaria incidence data, and predicted the future cause of the incidence. In this work, we incorporates climate variables in predicting malaria incidence using a technique called regression analysis with time series structure of stochastic term. But the work presented in [5], [17] uses univariate trend analysis of malaria incidence data and predicts the future cause of malaria, while [3] used support vector regression and random forests and compare their predicting capability from malaria incidence and climate data. However, the work presented in [15], [16] studied the physical influence of malaria incidence and its climatic predictors, and predicts the future incidence. Forecasting malaria incidence requires not only the use of incidence data and recorded climate information, but also investigation and understanding of the transmission at the micro-scale level. This can better achieved using the Disease Model Cradle (DMC) [1], [32], which uses daily times series of temperature and precipitation and explicitly simulates the gonotrophic cycle, sporogonic cycle and the interaction between mosquito and human.

In this study, we develop a model that incorporates climate predictors of malaria, with intention of investigating which of the predictors significantly contribute to high malaria incidence in a given geographical area. In this study, we apply the proposed model on the data concerning the monthly malaria incidence cases and climatic data from Aboh Mbaise region of Imo State–Nigeria with tropical and rain forest climate characteristics. The statistical significance of three climatic

factors, namely temperature, precipitation and relative humidity is examined by pre-whitening the climatic explanatory data and performing cross-correlation analysis with the malaria incidence data. Among these three factors, we find that relative humidity has the most statistically significant association (at probability, p-value < 0.05) with the malaria incidence data whereas temperature and precipitation have negligible lagged correlation with the incidence. Linear regression with autoregressive error structure AR(1) is then developed to precisely specify the relationship between the incidence and relative humidity time series. This finding is in contrast to some previous results [1], [12], [13] that highlight lagged contributions of temperature and precipitation and suggests variability in the strength of climatic factors in affecting malaria incidence in different geographical areas. This finding together with references [18], [19] can further motivate improvement of existing physical models of malaria-risk prediction like DMC [1] by incorporating comprehensive climatic variables.
The remaining parts of this paper are outlined as follows. In Section II, we present the methodology which comprises of study area, data collection and its presentation using the appropriate statistics. Section III discusses the regression analysis and diagnostic tests technique that are applied to the malaria incidence data and its climatic predictors. Section IV provides the discussion of our results that highlight the significance contribution of relative humidity to the high level of malaria incidence in Aboh Mbaise. Finally, we summarize our main findings in Section V.

II. Methodology

This study is focused on the analysis of confirmed cases of malaria incidence, together with satellite meteorological data on temperature, precipitation and relative humidity in Aboh Mbaise local government area of Imo State, Nigeria. The following present the materials and methods employed in this study.

A. Study area

The map of the Aboh Mbaise local government area (extracted from [24]) is shown in Fig. 1. The study area lies within Latitudes 5^0 $10^|$ N and 5^0 $51^|$ N also with Longitudes 6^0 $15^|$ E and 7^0 $28^|$ E, occupying land area of 184 km^2 [14]. The Aboh Mbaise, is one of the 27 local government areas of Imo State Nigeria. Aboh Mbaise community lives within a 15 km radius from the local government headquarters, with rain forest climate characteristics with average annual temperature above 20^oC (68^o F) and an annual relative humidity of 75% [28]. The rainy season begins in April and last until October with annual rainfall varying from 1,500 mm to 2,200 mm (60 to 80 inch). The dry season experiences two months of Harmattan from late December to late February and the hottest months are between Juanuary and March [32].

B. Data collection

The data used in this study, was extracted from the data presented in the literature of [20], and originally collected

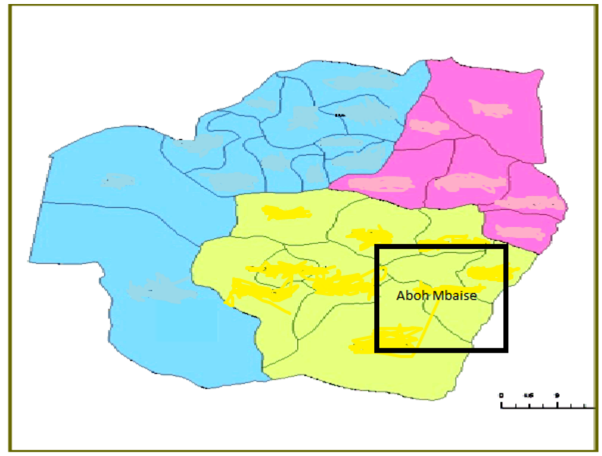

Fig. 1. The box indicated in the map, shows the location of the study area (Aboh Mbaise local government area, Imo State Nigeria).

from the Aboh Mbaise General Hospital. A total of 2,148 confirmed diagnosed cases of malaria incidence for the period of eighteen years, starting from January, 1996 to December, 2013 were collected. In order to have an insight on the possible climatic cause of high malaria incidence in the study area, we used the meteorological data. These data are not readily available at the time needed, within the reference weather station of Aboh Mbaise. Alternatively, we used satellite meteorological database through the following database: http://globalweather.tamu.edu/. The boundary metrics used in generating the data are Latitude 5.6556^0 N to 5.3494^0 S and Longitude 5.6291^0 W to 6.3776^0 E. Within the demarcation of the study area, one weather station was found. We generated daily minimum temperature, maximum temperature, precipitation and relative humidity for the period under study. The daily climate variables time series dimension is very large (6575) compare to monthly malaria incidence data which have less dimension (216). To ease the analysis, we converted the dimension of daily recorded climate data to monthly time series using ts() function in R, so as to pair the dimension with monthly malaria incidence data.

C. Data presentation

The data on confirmed diagnosed cases of malaria incidence is presented in Fig. 2 below, while climate variables data are presented in Fig. 5 in Appendix A.

The methods of data analysis employed in this study include: descriptive statistics, cross-correlation, pre-whitening and regression time series analysis, respectively . To determine lagged effect of the meteorological predictor variables on malaria incidence, we used cross-correlation analysis together with pre-whitening scheme to investigate the most significant predictor of malaria incidence. The autocorrelation function (ACF) and partial autocorrelation function (PACF) were used for identification of lags order of the time series models.

1) Summary statistics: Summary statistics of malaria incidence data and climate variables used in this study is presented in Table I. This summary would enable us to have

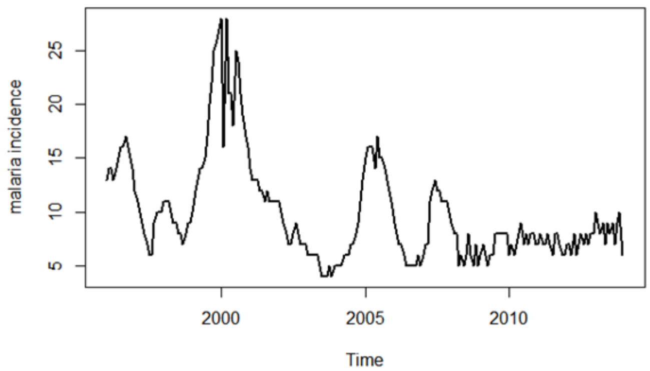

Fig. 2. The plot shows the pattern of monthly malaria distribution for the study area (Aboh Mbaise, Imo State Nigeria).

a structural understanding of the data components such as the variability, mean, minimum and maximum values. In addition, the summary statistics provides quick idea in the nature of data used.

TABLE I
SUMMARY STATISTICS FOR MONTHLY MALARIA CASES AND CLIMATE DATA

Variables	Mean	Std.	Min	Max
Malaria Data	9.94	4.80	4.00	28.00
Temperature	31.29	3.73	23.66	39.98
Relative humidity	7.92	9.53	0.00	73.31
Precipitation	3.00	1.00	2.00	4.00

2) Disease Model Cradle (DMC) [32]: is an epidemiological software designed for investigating and validating results with respect to field measurements, such as malaria incidence and the number of infected mosquitoes using Liverpool Malaria Model (LMM) together with meteorological datasets. The DMC interface provides space only for temperature and precipitation, and explicitly simulates the pattern of malaria incidence including micro-scale modelling [1].

As a benchmark in this study, we used meteorological datasets, temperature and precipitation for the Aboh Mbaise as an input into DMC software and simulated the outputs of malaria incidence, malaria prevalence, sporogonic cycle, gonotrophic cycle.

A key element of the DMC is the temperature-dependent mosquito survival options. The potential candidate for malaria transmission, that is adult mosquito, has three survival options within which its survive under the influence of temperature regime. The first survival option is called Martens scheme [12], [21] in which the daily survival probability (P) is linked to the temperature (T) as captured by the following second-order polynomial equation:

$$P(T) = -0.0016T^2 + 0.054T + 0.45. \qquad (1)$$

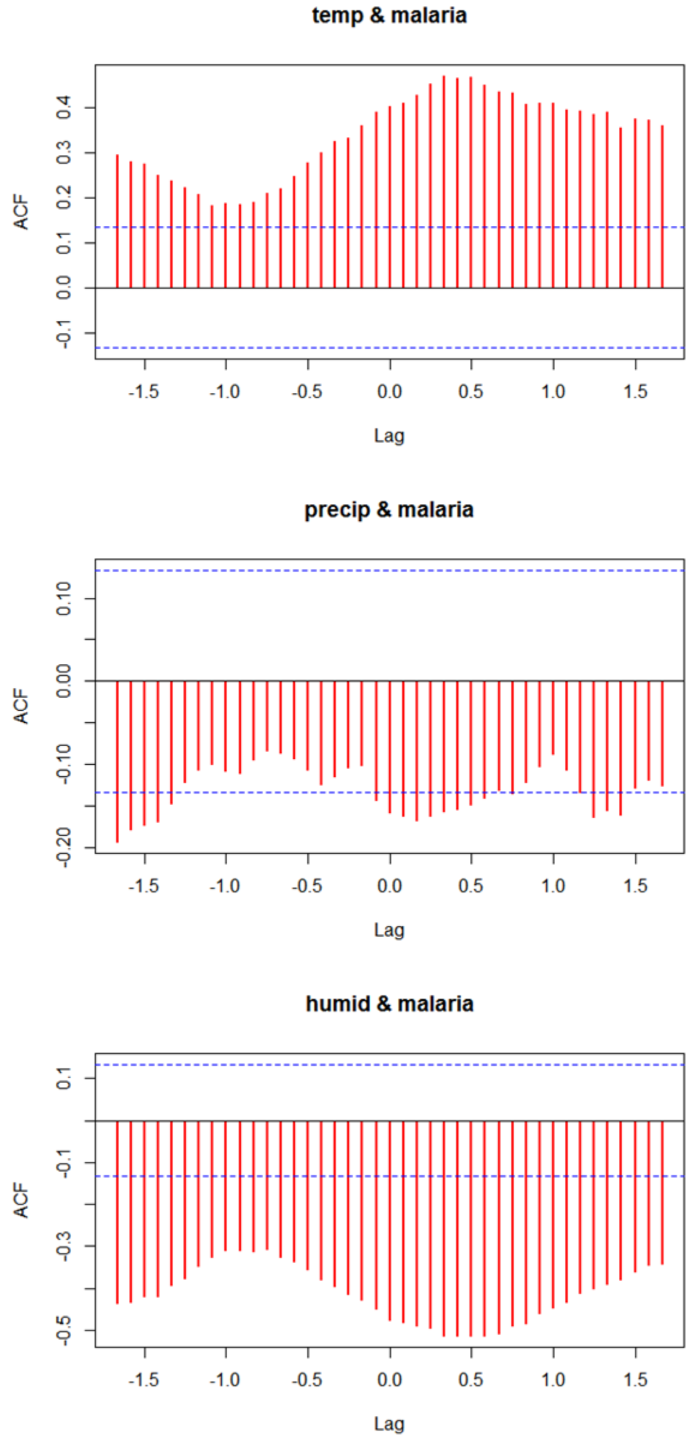

Fig. 3. The plots show the cross-correlation function between temperature and malaria incidence, precipitation and malaria incidence and relative humidity and malaria incidence, respectively.

The second survival option is called Lindsay and Birlay scheme [22], which uses a fixed probability per gonotrophic cycle as:

$$P = \exp\left(\frac{P_{lb}}{T_g}\right) \tag{2}$$

where: P_{lb} is the survival per cycle, and T_g is the length of gonotrophic cycle. The third survival option is called Craig scheme [23], which links the survival probability (P) with an exponential function of the temperature (T) as [21]

$$P = \exp\left(\frac{-1}{-4.4 + 1.31T - 0.03T^2}\right). \tag{3}$$

III. Regression Analysis

Previous studies [1], [12], [13] have shown that climate variables like temperature and precipitation have lagged effects on the occurrence of malaria transmission, while the relative humidity does not have that effects. Another study [27] showed that relative humidity may have an impact to the malaria transmission as it supports the vector (mosquito) by providing a suitable atmosphere to survived longer. These different observations suggest that the strength of each climatic factor may vary from one geographical area to another. In the context of our study area, we determine the significant (lagged and non-lagged) contributing factors by invoking cross-correlation function (CCF) as follows.

A. Cross-Correlation Function (CCF)

CCF can be considered to be a useful tool for determining the most influential climatic variable to predict the occurrence of malaria and mathematically expressed by [28]

$$c_{uy}(k) = \frac{1}{N}\sum_{t=1}^{N-k}(u_t - \overline{u})(y_{t+k} - \overline{y}) \tag{4}$$

for $k = 0, 1, ...(N-1)$

$$c_{uy}(k) = \frac{1}{N}\sum_{t=1-k}^{N-k}(u_t - \overline{u})(y_{t+k} - \overline{y}) \tag{5}$$

for $k = -1, -2, ..., -(N-k)$ as the product-moment correlation of time-offset or a function of lag between two time series $\{u_t\}_t$ and $\{y_t\}_t$. Herein N is the series length, $\overline{u}$ and $\overline{y}$ are the sample means, and k is the CCF lag. Hence the cross-correlation function is also auto covariance function when scaled by the variances of the two series as:

$$r_{uy}(k) = \frac{c_{uy}(k)}{\sqrt{c_{uu}(0)c_{yy}(0)}} \tag{6}$$

where $c_{uu}(0)$ and $c_{yy}(0)$ are the sample variances of u_t and y_t, respectively.

CCF between climatic variables and malaria incidence data is depicted in Fig. 3, which aims to aid in identifying the lags of the climatic predictors that might be a useful predictor of malaria incidence. However, the three plots show a pattern that is difficult to identify any lagged effects of the climate predictor of malaria. This difficulty happens due to the fact that CCF values are sometimes affected by the time series structure of the independent variable against dependent variable series over time.

B. CCF with Pre-Whitened Climatic Data

In order to alleviate the difficulty of identifying the significant lags of the climatic predictors in Fig. 3, we invoke a pre-whitening technique in order to stationarize the climatic input variables. When the input series behaves like white noise,

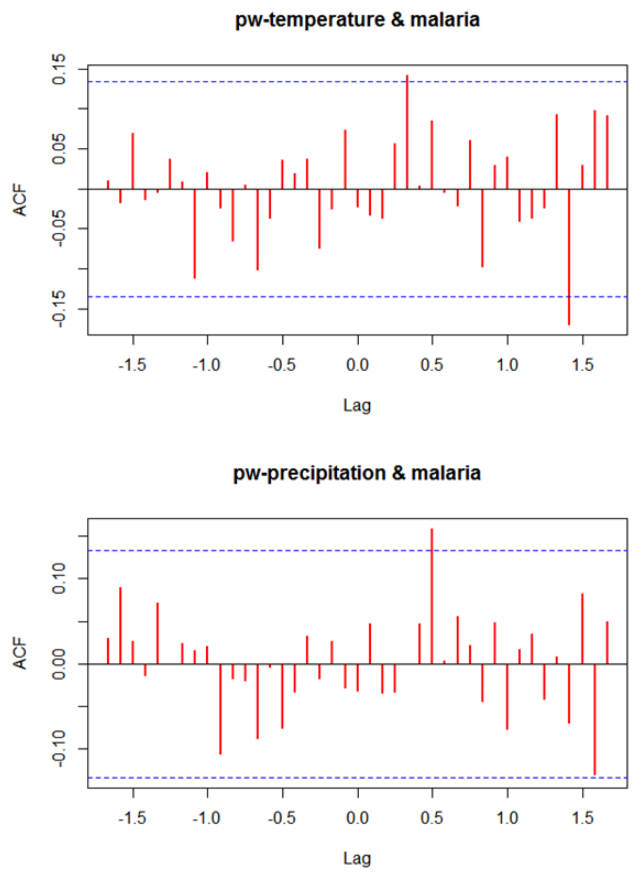

Fig. 4. The plots indicates pre-whitened lagged correlations between temperature with malaria incidence and precipitation with malaria incidence.

and the pattern of the CCF between climate variables and malaria incidence is a linear combination of lags of the input variables. Incorporation of pre-whitening for the time series of interest involves the following steps. Firstly, we determine the time series model for the malaria predictor variables and store the residuals from the model. Secondly, we filter the malaria incidence variable using the model of the predictors. Thirdly, we examine the CCF between the residuals of the predictors and the filtered values. Hence, the resultant CCF can be used to identify the possible pattern for lagged effects that would be used in regression model.

Using autocorrelation function (ACF) and partial ACF (PACF) of climatic-predictors after differencing operation, we obtain estimated time series models for temperature and precipitation data as tabulated in Table II. The resulting time-series model of temperature is estimated to be ARIMA (1,1,0), which is autoregressive moving average model for order 1, with differencing order of 1. The estimated coefficient param-

TABLE II
PRE-WHITENED MODELS FOR TEMPERATURE AND PRECIPITATION TIME SERIES

Pre-whitened model	Estimates	Standard Error
ARIMA(1,1,0)	-0.343	0.064
Log-likelihood	-473.65	
AIC	951.3	
ARIMA(2,1,0)	-0.3291	0.0654
	-0.2755	0.0652
Log-likelihood	-784.08	
AIC	1574.14	

eter for this ARIMA (1,1,0) model is given by $\hat{\theta} = -0.343$, which leads to the estimated model:

$$\Phi_T(B)y_t = \epsilon_t \tag{7}$$

where

$$\Phi_T(B) = (1 - 0.657B - 0.343B^2). \tag{8}$$

Similarly, aided by the plots of ACF and PACF after differencing operation, the precipitation time series is approximated to be ARIMA (2,1,0) model, which can be represented by

$$\Phi_P(B)z_t = \epsilon_t \tag{9}$$

where

$$\Phi_P(B) = (1 - 0.6709B - 0.0536B^2 - 0.2755B^3). \tag{10}$$

The time series defined by the polynomial $\Phi_T(B)$ and $\Phi_P(B)$ have been found stationary by inspection, which confirm that temperature and precipitation time series achieve stationarity after taking the first differences.

Once the time series models for temperature and precipitation are determined, the next stage is the filtering process, which involves filtering the malaria incidence data using the aforementioned time series models. We continue by examining the CCF between the residuals from the time series models for the climatic input variables and the filtered malaria incidence to identify the significant lagged terms of the regression model. From the pre-whitened CCF plots in Fig. 4 of temperature time series with malaria incidence and precipitation time series with malaria incidence, we observe that, the most significant spike in both plots appeared on the positive lags segments of the cross-correlation function indicating an overlapping effects. Therefore, this shows an evidence that there is no significant lagged effects of temperature and precipitation effectively predicts the occurrence of malaria in the study area.

C. Regression Model

By taking into account the three climatic predictors (temperature, precipitation and relative humidity), we propose a regression model that predicts the pattern of malaria incidence occurring in Aboh Mbaise:

$$\begin{aligned} MI_t =& \beta_o + \beta_1 f(TM_{t-1}TM_{t-2}) + \beta_2 g(PR_{(t-1)}) \\ &+ \beta_3 RH + \epsilon_t \end{aligned} \tag{11}$$

where MI denotes the Malaria incidence as the output of the model, and TM, PR and RH denote temperature, precipitation and relative humidity, respectively as the inputs of the model. Herein β_1, β_2 and β_3 are coefficients of the regressed variables, β_o is intercept, ϵ_t is error term.

From the results of pre-whitening analysis of the predictor variables presented in Table II, we found that temperature and precipitation have insignificant lagged effects on malaria incidence. Based on that, we can drop their effects on the model to avoid redundancy. Hence, the regression model can be compactly expressed as:

$$MI_t = \beta_o + \beta_3 RH_t + \epsilon_t \tag{12}$$

Using the least squares method, we obtained the estimate of the model as:

$$MI_t = 31.212 - 25.467RH_t \tag{13}$$

In modelling regression using time series variables, it is very natural for the residuals to have a time series structure. However, using the conventional approach (least squares method), such an assumption of independent error is violated. Hence, the consequence is the wrong estimates of coefficients and their standard errors if the time series structure of the errors is ignored. Therefore, we need to adjust the regression coefficients and standard errors in order to have a well-fit regression model, including the component of AR error structure.

Suppose, let us consider the following equation to illustrate the adjustment of regression coefficients and standard errors for a simple case and use its to advance in our analysis

$$y_t = \beta_o + \beta_1 x_t + \epsilon_t \tag{14}$$

where the autoregressive structure of error is captured by

$$\epsilon_t = \vartheta_1\epsilon_{t-1} + \vartheta_2\epsilon_{t-2} + \ldots + \omega_t \tag{15}$$

where $\omega_t \sim$ i.i.d. $\mathcal{N}(0, \sigma^2)$. Then, let

$$\varphi(L) = 1 - \vartheta_1 L - \vartheta_2 B^2 - \ldots, \tag{16}$$

denotes the AR model for the errors which reduces to $\varphi(L)\epsilon_t = \omega_t$. If we assume the inverse of $\varphi(L)$ exists, we have $\epsilon_t = \varphi^{-1}(L)\omega_t$, where $\omega_t \sim$ i.i.d. $\mathcal{N}(0, \sigma^2)$. Therefore, we can write (14) as:

$$y_t = \beta_o + \beta_1 x_t + \varphi^{-1}(L)\omega_t \tag{17}$$

such that $\varphi(L)$ gives the AR polynomial for the errors.

If we multiply (17) by $\varphi(L)$, we obtain

$$\varphi(L)y_t = \varphi(L)\beta_o + \beta_1\varphi(L)x_t + \omega_t. \tag{18}$$

Let

$$y_t^* = \varphi(L)y_t = y_t - \vartheta_1 y_{t-1} - \ldots - \vartheta_p y_{t-p} \tag{19}$$

$$x_t^* = \varphi(L)x_t = x_t - \vartheta_1 x_{t-1} - \ldots - \vartheta_p x_{t-p} \tag{20}$$

$$\beta_o^* = \varphi(L)\beta_o = (1 - \vartheta_1 - \ldots - \vartheta_p)\beta_o. \tag{21}$$

We can then write the model as:

$$y_t^* = \beta_o^* + \beta_1 x_t^* + \omega_t \tag{22}$$

where $\omega_t \sim$ i.i.d. $\mathcal{N}(0, \sigma^2)$. Note that the unknown constant β_o in (17) does not depend on the time and is also independent of shifting operation. We can approximate this β_o by

$$\hat{\beta}_o = \frac{\hat{\beta}_o^*}{1 - \hat{\vartheta}_1 - ... - \hat{\vartheta}_p}. \tag{23}$$

Similarly, the standard error for $\hat{\beta}_o$ is given as

$$s.e(\hat{\beta}_o) = \frac{s.e(\hat{\beta}_o^*)}{1 - \hat{\vartheta}_1 - ... - \hat{\vartheta}_p} \tag{24}$$

Reference [31] developed this procedure, and the process is repeated until the estimates converges. Following the methodology of [31], and the adjustment of the regression model for predicting malaria incidence can be presented as:

$$y_t^* = -0.0896 - 0.8902 y_{t-1}^* \tag{25}$$

$$x_t^* = -0.0896 - 0.8902 x_{t-1}^* \tag{26}$$

Thus, the estimated relationship between malaria incidence and relative humidity in the study area is given by

$$MI_t = 30.095 - 25.387 RH_t + \epsilon_t, \tag{27}$$

where the error term can be expressed as

$$\epsilon_t = 0.9236 \epsilon_{t-1} + \omega_t, \tag{28}$$

where $\omega_t \sim$ i.i.d. $\mathcal{N}(0, 3.773)$. We present the model accuracy in Table III, for both the model without AR structure errors and the adjusted model with AR structure errors.

TABLE III
MODEL ACCURACY

Model	RMSE	MAE	MAPE	MASE
Without AR errors	4.2100	2.9664	32.5958	0.8158
With AR errors	3.7556	2.6482	32.2130	0.8176

IV. Discussion of Results

In this section, we discuss the results of the analysis using the Rstudio version 0.99.902 and DMC.

From the results of CCF between malaria incidence and pre-whiten climate variables in the study area, we find that temperature and precipitation have negligible lagged effects with the occurrence of malaria. Temperature supports parasites development speed within mosquito and also its morphological stage. While precipitation creates breeding sites for mosquitoes to lay their eggs and supports its survival in the water body. The study area experiences the rainy season, beginning in April and last until October with annual rainfall varying from 1,500 mm – 2,000 mm (60 to 80 inch). The annual temperature is above 20^{o}C (68^{o}F) and an annual relative humidity is about 75%. The temperature and precipitation data in the study area have exceeded the threshold to become predictor of malaria incidence, but in contrary they have negligible influence. We therefore attribute this to a huge amount of rain that washes out the ground and kills the eggs [25] and [26]. It is understood that sustained rainfall provides breeding sites for mosquitoes, and thereby increases its population. We run analysis of variance on the regression model established between malaria incidence and climate variables, and find that at probability (p-value < 0.05), indicating a statistically significance level that relative humidity seems to be a dominant climate predictor of malaria in the study area. The relative humidity may be determined by precipitation. From the available information, that relative humidity in the study area reaches 90% during rainy season than dry season. Relative humidity is a climatic variable that does not support the mosquitoes sporogonic cycle or gonotrophic cycle but it only strengthens the vector longevity and also provides a good atmosphere for bitting [27] especially in the night hours. The study area has a rain forest vegetation belt, which shows an indication of a high level of relative humidity.

Simulation analysis was conducted using DMC for each of the three survival schemes. The DMC model was initialized with default parameter values, and we generates the effects of malaria transmission based on temperature and precipitation for individual years. The simulation results show no lagged response of malaria incidence with temperature and precipitation in the study area.

V. Conclusion

We have analysed the data on confirmed diagnosed case of malaria and together with climate variables (temperature, precipitation and relative humidity) in order to gain insights on which of the climate variables contribute significantly to the high malaria incidence in Aboh Mbaise local government area of Imo State, Nigeria. We have used a pre-whitening scheme and cross-correlation analysis for identification of lagged effects of the climate variables that predict the malaria incidence in the study area. From the analysis of CCF, we have found that temperature and precipitation have no lagged effect on the occurrence of malaria, and were dropped out from the model to avoid redundancy. Furthermore, this no lagged effect has been further confirmed by simulation analysis using DMC. The results from the regression analysis show that relative humidity is highly significant at probability (p-value $<$ 0.05). Considering the distribution of monthly average relative humidity in the study gives an insight that relative humidity seems to be a dominant predictor of malaria incidence. A regression model has been established between the malaria incidence and relative humidity to predict the occurrence of malaria incidence in the study area.

Climate variables are out human control in controlling the transmission of malaria in the study area, but can be used as a prior information as an early warning signal to alert the vulnerable. In this study, we found relative humidity is the most influential climate predictor of malaria in the study area.

Acknowledgment

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Appendix A
Plot of Climatic Data from 1996–2013

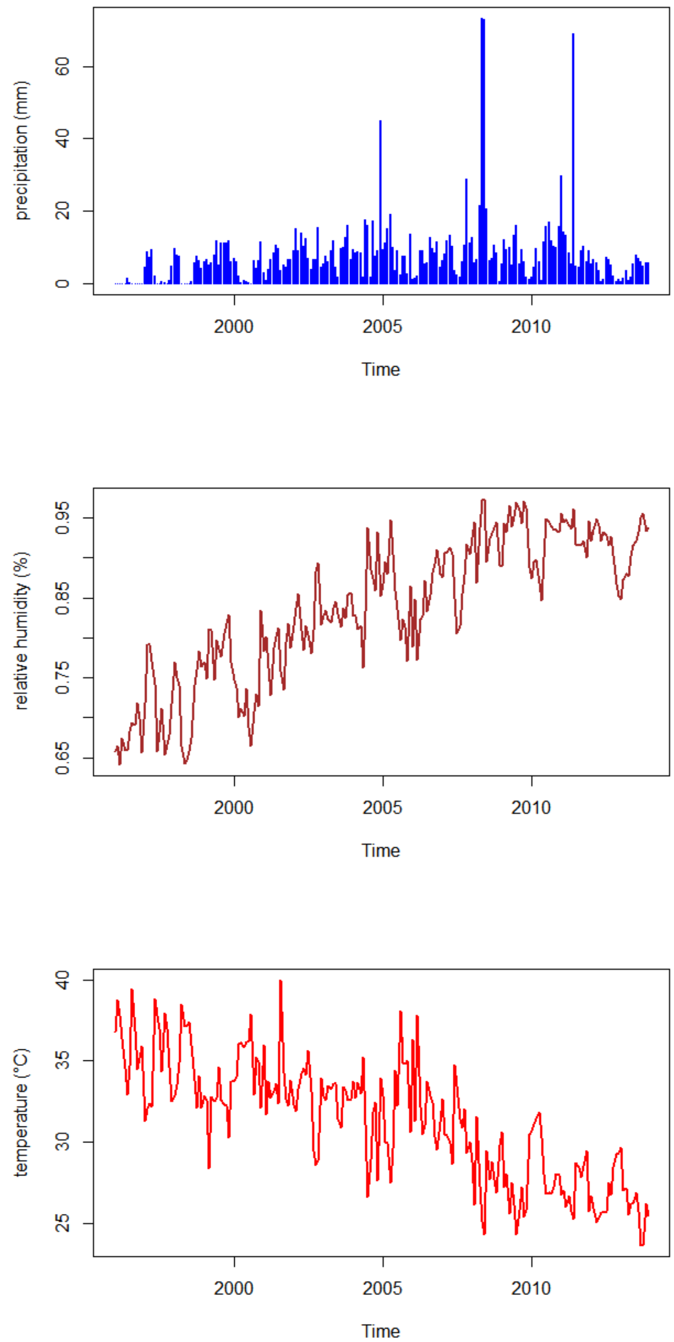

Fig. 5. Time series plots showing the pattern of monthly distribution of climate variables in the study area.

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