Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2020, 7(2):131-141**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Change Detection in Malaria Mortality Cases in the Northern Region of Ghana using Intervention Analysis

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Abstract In this study, we investigated the effects of various malaria control interventions mortality (deaths) in the Northern Region of Ghana through intervention analysis. A model for predicting the number of deaths due to malaria in the region was also determined. Data on monthly mortalities due to malaria were obtained from the Northern Regional Health Directorate. The results revealed that, ARIMAX (1, 1, 1) was the best model with the least Akaike Information Criterion (AIC), Akaike Information Criterion corrected (AICc) and Bayesian Information Criterion (BIC). Diagnostic checks of the model with the Ljung-Box test and Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH-LM) test revealed that the model was free from higher-order serial correlation and conditional heteroscedasticity respectively. A cumulative sum (CUSUM) test on the residuals of the model also revealed that the model was structurally stable over time. A chi-square goodness of fit test also revealed that there was no significant difference between the predicted values from the model and the observed values for the year 2018. The study further revealed that the coefficient of the intervention variable was negative signifying that the interventions brought about a decline in the number of mortalities due to malaria in the region.

Keywords Malaria, Intervention, Autoregressive Moving Average with an Independent variable (ARIMAX), Cumulative Sum (CUSUM), Lujung-Box and Heteroscedasticity

1. Introduction

The problem of malaria has remained an issue of concern in sub-Saharan Africa for so many years. According to Ghana Health Service (GHS) facility data, malaria is the number one cause of morbidity and mortality in children under five years of age, currently accounting for 33% of hospital deaths in children under five, about 38% of all outpatient illnesses and 36% of all admissions. Between 3.1 million and 3.5 million annual cases of clinical malaria are reported in public health facilities, 900,000 cases are in children under five years and 3,000-4,000 result in inpatient deaths [1]. Thus malaria has led to the loss of countless vital lives in the country. The survival of these lives could have been very beneficial to the development of Ghana through their contributions in various sectors of the economy. Due to the considerable loss of lives due to malaria, the government of Ghana through the Ministry of Health and the Ghana Health Service has been instrumental in curbing it; through the implementation of intervention measures. These interventions include: improving access to prompt and effective treatment, strengthening health systems at all levels, and creating and sustaining partnership in the health sector. The interventions are aimed at reducing deaths and illnesses due to malaria by 75 per cent by the year 2018 so that the disease is no longer of public health significance.

We therefore employed the Autoregressive Integrated Moving Average model with an independent variable as an intervention variable (ARIMAX) in this study to investigate the effects of these interventions on the number of mortalities due to malaria in the Northern Region of Ghana. A model for predicting the number of deaths in the region shall also be determined.

The study will serve as a guiding tool to policy makers such as the Ministry of Health (MoH) and Ghana Health Service (GHS), and multilateral organizations in the health sector in making informed and intelligent policy decisions in the fight against malaria and other public health diseases in the country.Further, the information uncovered from this study when put into better and effective use in combating malaria would have the economic benefit of saving cost in the region and the nation at large. Lastly, the Regional Health Directorate (RHD) would benefit immensely from accurate forecasts of the malaria disease burden within this part of the country.

Myriad of researches have been carried out all over the world on malaria morbidity and mortality. [2] modelled and forecasted malaria mortality rate in the AbohMbaise General Hospital, Imo State in Nigeria. They employed the Box-Jenkins methodology to build an ARIMA model for the malaria mortality rate from January 1996 to December 2013.They used the fitted model to forecast monthly malaria mortality rate for the year 2014.

Further, [3] used time series analysis to investigate the relationship between falciparum malaria in the endemic provinces and imported malaria in the non-endemic provinces of China. Several Autoregressive Integrated Moving Average (ARIMA) models were fitted to the predictor variable and tested, and it was revealed that ARIMA (1, 1, 1) and (0, 1, 1) models for malaria incidence fitted the data best according to the AIC and goodness-of-fit criteria.

Moreover, [4] formulated a model for short term malaria prediction in Sri Lanka. Exponentially moving average models, ARIMA models with seasonal components and seasonal multiplicative ARIMA models were compared on monthly time series of district malaria cases for their ability to predict the number of malaria cases one to four months ahead. The results showed that the best model for forecasting and forecasting error varied significantly among the districts.

Also, [5] carried out a research using Generalized Seasonal Autoregressive Integrated Moving Average (GSARIMA) models for count data with application to malaria time series with low case numbers in Sri Lanka. The models were applied to monthly malaria case time series in a district in Sri Lanka, where malaria had decreased drastically in recent years. The results revealed that the malaria series showed long-term changes in the mean, unstable variance and seasonality. They concluded that GSARIMA models may be particularly useful in the drive towards malaria elimination, since episode count series are often seasonal and non-stationary, especially when control is increased.

Again, [6] conducted a research on the topic: "Forecasting malaria incidence from historical morbidity patterns in epidemic-prone areas of Ethiopia: a simple seasonal adjustment method performs best". The aim of this study was to assess the accuracy of different methods of forecasting malaria incidence from historical morbidity patterns in areas with unstable transmission. Five methods were tested using incidence data reported from health facilities in 20 areas in central and north-western Ethiopia. The study showed that simple seasonal adjustment methods outperformed a statistically more advanced ARIMA method. In particular, a seasonal adjustment method that uses mean deviation of the last three observations from expected seasonal values consistently produced the best forecasts.

Also, a research was carried out by [7] on the development of temporal modelling for forecasting and prediction of malaria infections using time-series and ARIMAX analyses in endemic districts of Bhutan. The study was carried out retrospectively using the monthly reported malaria cases from the health centres to Vector-borne Disease Control Programme (VDCP) and meteorological data from Meteorological Unit, Department of Energy, and Ministry of Economic Affairs. Time series analysis was then performed on monthly malaria cases, from 1994 to 2008, in seven malaria endemic districts. The time series models derived from a multiplicative SARIMA was employed to identify the best model using data from 1994 to 2006. Hence the best-fit model was selected for each individual district and that of the overall endemic area was also developed. In developing the prediction model, the monthly reported malaria cases and the meteorological factors from 1996 to 2008 of the seven districts were analysed. The method of ARIMAX modelling was then employed to determine predictors of malaria of the subsequent month.

Also, [8] assessed the steep decline of malaria morbidity and mortality trends in Eritrea between 2000 and 2004. This study examined the impact of Eritrea's Roll Back Malaria Programme (2000-2004) and the effects and possible interactions between the public health interventions in use. The study employed cross-sectional survey to collect data from households, community and health facilities on coverage and usage of ITNs, IRS, larvicidal activities and malaria case management. An ARIMA model was used to assess association. The study showed thatin the period 2000-2004, there was a substantial increase in IRS coverage, distribution of ITNs, and also the number of health workers and community health agents trained had risen significantly. The correlation between malaria case fatality and ITNs, IRS, population protected and annual rainfall was however not statistically significant.

Also, [9] employed the SARIMA intervention time series analysis to investigate the effect of malaria control intervention in the KwaZulu-Natal Province in South Africa. The intervention was the re-introduction of dichlorodiphenyltrichloethane (DDT) on confirmed malaria cases. The result showed an abrupt and permanent decline of malaria cases following the implementation of the intervention policy.

Again, [10] carried out a research on forecasting future malaria incidence in the Kumasi Metropolis, Ghana using ARIMA models. Trends of malaria prevalence was analysed and compared by years and months. It was revealed that July had the highest number of cases whereas January recorded the lowest number of cases. The predicted numbers of cases for the first and second halves of the year 2018 were 61, 371.8 and 77,842.0 respectively.

Also, [11] used the Box-Jenkins SARIMA model approach to investigate monthly malaria infections in the Kass Zone, South Darfur State, Sudan. An ARIMA forecasting model was obtained from the analyses to predict the monthly malaria infections.

Furthermore, [12] researched on time series analysis of malaria cases in the KasenaNankana Municipality, Navrongo, Ghana. They developed an ARIMA model that can adequately forecast future trends of malaria cases in the Municipality.

Additionally, [13] also used time series ARIMA models to predict future trends in malaria incidence in Afghanistan. Two (2) predictive models were obtained that can accurately forecast malaria incidence in that country. Enhanced vegetation index was also found to have increased the predictive accuracy of the models in the long-term.

Additionally, [14] used vector autoregression (VAR) to model the impact climatic variability malaria in Ghana. The study revealed that malaria is highly influenced by three (3) main climatic variables that include maximum temperature, rainfall and humidity. Again, Perez and Ceballos [15] conducted a study to develop an appropriate model that could predict the weekly reported malaria incidence in the Philippines using the Box-Jenkins method. Based on the results of their analysis, ARIMA (2, 1, 0) was selected as the model for predicting the weekly malaria incidence in the Philippines.

It can be observed from the above review that several approaches have been used to model and forecast malaria morbidity and mortality in various parts of the world. There is however no known research conducted on malaria mortality using time series intervention analysis models in the Northern Region of Ghana. This research will therefore employ the intervention analysis models developed by [16] to assess the effects of the various malaria control intervention programmes in the northern region of Ghana and to obtain a monthly mortality forecasting model.

2. Methodology

Data on monthly mortality cases to due malaria was obtained from the Northern Regional Health Directorate and used to undertake this study. The data covered the period of January 2004 to December 2018. January 2004 to December 2007 was considered as the pre-intervention period whereas January 2008 to December 2018 was the post intervention period. The data from January 2004 to December 2017 was used to carry out the analyses whilst that of 2018 was used for cross validation. The data was ran using Minitab, R and Grtl, and was modelled using ARIMAX models. Preliminary tests to determine the presence or absence of stationarity and unit roots were then carried out and results were finally modelled using an ARIMAX model.

2.1 Unit Root Test

Stationarity is an indispensable aspect of time series analysis. Several approaches have been developed to test for the stationarity or otherwise of a time series data which include both graphical and quantitative approaches. In this study however, we employed two quantitative methods including the Augmented Dickey-Fuller (ADF) [17] test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [18] test. The presence of a unit root signifies that the time series is not stationary and that differencing needs t0o be done in order to reduce it to stationarity.

2.1.1 Augmented Dickey Fuller (ADF) Test

The ADF test tests the null hypothesis that a unit root is present in a time series sample. It has the advantage of handling a larger and more complicated set of time series models. The ADF test was developed to deal with serial correlations in the time series since it does not suffer size distortions under over parametizations, extreme autocorrelation, and increased sampling frequency. The test is based on the regression of the observed variable Y_t on its one-period lagged value Y_{t-1}, and sometimes includes an intercept and a time trend. The ADF model is given as:

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \cdots + \gamma_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \qquad (1)$$

Where Δ is the difference operator, implying that $\Delta Y_t = Y_t - Y_{t-1}$, $\delta = \phi - 1$, α is a constant, β the coefficient on time trend series, $\gamma_1 \Delta Y_{t-1} + \cdots + \gamma_{p-1} \Delta Y_{t-p+1}$ is the sum of the lagged values of the dependent variable ΔY_t and p is the lag order of the AR process. The ADF test is concerned with the value of the parameter δ. If $\delta = 0$, it presupposes that the series contains unit root and hence non-stationary.

The test statistic for the ADF test is given by:

$$\mathrm{F}_\tau = \frac{\hat{\delta}}{\mathrm{SE}(\hat{\delta})} \qquad (2)$$

Where $\hat{\delta}$ is the least square estimate and$\mathrm{SE}(\hat{\delta})$ is the standard error estimate of $\hat{\delta}$. If the calculated value of the test statistic is greater than the critical value, we reject the null hypothesis of $\delta = 0$.

2.1.2 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test has a null hypothesis of stationarity of a series around either the mean or a linear trend; and the alternative assumes that the series is non-stationary due to the presence of a unit root.

The test statistic of the KPSS test is given by;

$$KPSS = \sum_{t=1}^{T} \frac{S_t^2}{\sigma_\infty^2} \qquad (3)$$

Where T denotes the number of observations, $S_t = \sum_{i=1}^{t} \varepsilon_i$, for $t = 1,2, \ldots, T$, ε_i denotes estimated errors from a regression of Y_t on a constant and time and are computed as: $\varepsilon_t = Y_t - \bar{Y}$and $\hat{\sigma}_\infty^2$ is an estimator of the long-run variance of the ε_t process given as:

$$\sigma_\infty^2 = \lim_{T \to \infty} T^{-1} Var(\sum_{t=1}^{T} \varepsilon_t) \qquad (4)$$

Or

$$\sigma^2 = limT^{-1} E[S_T^2] \qquad (5)$$

The decision rule is to reject the null hypothesis of stationarity if the computed value of the test statistic is greater than the critical value at a given level of significance.

2.2. Regression with ARIMA Errors (ARIMAX Model)

In addition to past values of the response series and past errors, we can also model the response series using the current and past values of other variables, called input variables. ARIMA models with input variables are referred to as regression with ARIMA errors or ARIMAX model. The model therefore combines a regression model with an ARIMA model. The regression component describes the explanatory relationship of the variables whereas the ARIMA component deals with the autocorrelation in the residuals of the regression model. An ARIMAX model is given by:

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \frac{\theta(B)\Theta(B^s)}{\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D}\varepsilon_t \qquad (6)$$

2.3. Criterion for Model Selection

In order to obtain the most adequate model that best describes a time series data, it is imperative for model selection criteria to be carried out. This is because there is the possibility of two or more models to compete in the selection of the best model. The AIC, AICc and the BIC [19] were the model selection criteria employed in this study to select the most adequate model. The best model is the one with the smallest AIC, AICc or BIC values, given a set of candidate models. The AIC, AICc, and BIC are generally given by;

$$\text{AIC} = 2k - 2In(L) \qquad (7)$$

$$\text{AICc} = \text{AIC} + \frac{2k(k+1)}{n-k-1} \qquad (8)$$

$$\text{BIC} = \log(\sigma_e^2) + \frac{k}{n}\log(n) \qquad (9)$$

Where k represents the number of parameters in the model, L denotes the maximised value of the likelihood function, n is the number of observations in the data and σ_e^2 is the error variance.

2.4. Model Diagnostics

After a model has been built, it is important to diagnose the model in order to ensure that it truly reflects the real time series observations. When these checks are done the model can be used to make meaningful generalisations or to draw inferences. The Ljung-Box, ARCH-LM and the CUSUM tests were employed in this study to diagnose the adequacy of the developed model.

2.4.1. Ljung-Box Test

The Ljung-Box [20] test was used to determine the presence or absence of serial correlation in the time series up to a given order say k. The test statistic is given by;

$$Q_h = n(n+2)\sum_{k=1}^{h}\frac{r_k^2}{n-k} \qquad (10)$$

Where r_k^2 represents the residual autocorrelation at lag k, n is the number of residuals and h is the number of lags being tested. We reject the null hypothesis if Q_h is greater than the chi-square table value. The model is therefore considered adequate when the p-value associated with Q_h is large.

2.4.2. ARCH-LM Test

The Ljung-Box test was developed by Ljung and Box [21] as a diagnostic tool to examine autocorrelations of the residuals of a fitted model.The test is used to deal with the issue of conditional heteroscedasticity when fitting models. This problem occurs when the residuals do not have a constant variance. Therefore the assumption of constant variance must be met in order to obtain an adequate model. The test statistic is given as:

$$\text{LM} = nR^2 \qquad (11)$$

Where n is the number of observations and R^2 is the coefficient of determination of the auxiliary residual regression. This is given by:

$$e_t^2 = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 e_{t-2}^2 + \ldots + \beta_q e_{t-q}^2 + v_t \qquad (12)$$

Where e_t is the residual. The null hypothesis is rejected when the p-value is greater than the level of significance and hence we conclude that there is no heterosdasticity in the model residuals.

2.4.3. CUSUM Test

In fitting a good model, it is imperative also to check the stability of the model over time. The CUSUM test was therefore developed for the study of structural stability of models and the test statistic was constructed based on cumulated sums of recursive residuals. The test statistic is given by:

$$\text{CUSUM}_\tau = \sum_{t=K+1}^{\tau}\frac{\hat{u}_t^{(r)}}{\hat{\sigma}_u} \qquad (13)$$

Where $\hat{u}_t^{(r)}$ are the recursive residuals and $\hat{\sigma}_u$ is the standard error of the regression fitted to all T sample points and $\tau = K+1, \ldots, T$. There is evidence of structural instability of the model in question if the CUSUM wanders off too far from the zero line. At a 5% significance level, we reject stability given that CUSUM_τ crosses the lines $\pm 0.948[\sqrt{T-K} + 2(\tau - K)/\sqrt{T-K}]$ [22].

2.4.4. Jarque-Bera (JB) Test

Normality is a common assumption in many statistical analyses. Hence testing the normality of a distribution has become a standard feature in many statistical works [23]. This study therefore employed the JB test to confirm the normality of the data. The JB test is very useful when the sample size is large (greater than 2000). The test statistic is given as:

$$JB = n[\frac{S^2}{6} + \frac{(K-3)^2}{24}] \quad (14)$$

Where n= sample size, S= coefficient of Skewness and K= coefficient of kurtosis

The JB test has a chi-square distribution with two degrees of freedom. Hence, we reject the null hypothesis of normality if $JB > X^2$ calculated value.

3. Results and Discussion

The KPSS and ADF tests for unit roots were carried out to determine the stationarity or otherwise of the series. The KPSS test results shown in Table 1 revealed that the calculated value is greater than the critical value at 5% level of significance. We therefore reject the null hypothesis of stationarity indicating that the series is not stationary.

Table 1: KPSS test for Mortality cases

Case	Test Statistic	Critical value
Death	1.3538	0.4650

Also, the ADF test carried out with only a constant term and a constant with quadratic trend affirmed the presence of unit roots in the series, since the *p*-value was greater than the 0.05 level of significance as illustrated in Tables 2.

Table 2: ADF test for Mortality cases

Case	Constant		Constant + Quadratic Trend	
	Test Statistic	*P*-value	Test Statistic	*P*-value
Death	-0.3795	0.9104	-1.9699	0.8285

There was no evidence of seasonality observed in the ACF plot of the series since there were no significant spikes. Hence it was transformed logarithmically and then differenced non-seasonally before being tested again for stationarity. The transformed and non-seasonal differenced series for the Death cases revealed stationarity in the series as illustrated in Tables 3 and 4.

Table 3: KPSS test for non-seasonal differences of Mortality cases

Case	Test Statistic	Critical value
Death	0.0348	0.4650

Table 4: ADF test for non-seasonal differences of Mortality cases

Case	Constant		Constant+ Quadratic Trend	
	Test Statistic	*P*-value	Test Statistic	*P*-value
Death	-5.0960	0.0013	-5.5933	0.0070

The time series plot of the transformed and non-seasonal differenced series for the Deaths shown in Figure 1 also affirms that the series is now stationary in the mean and variance due to the fluctuations about the zero line.

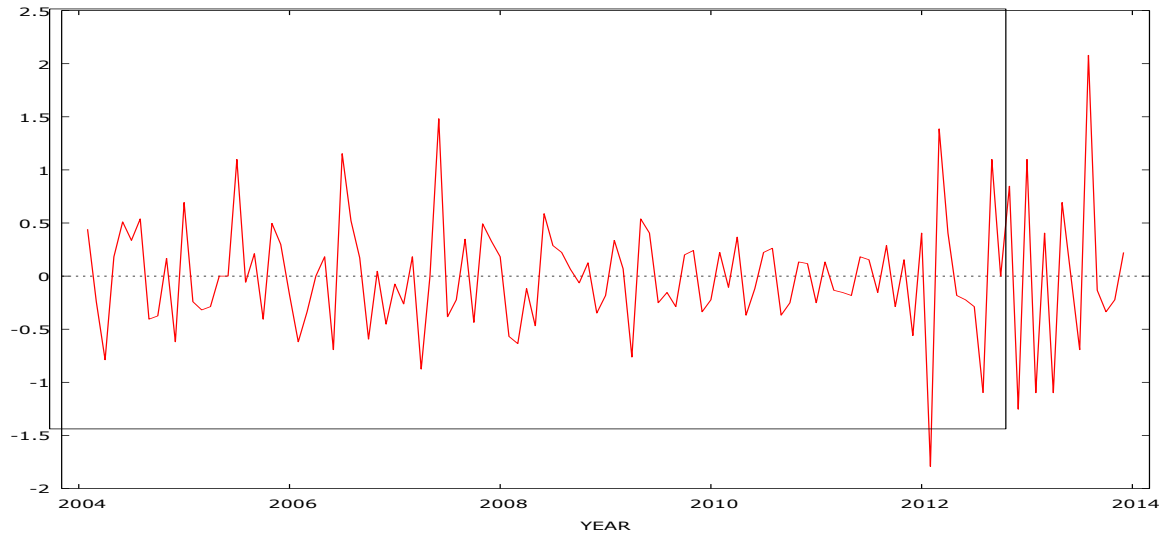

Figure 1: Time series plot of Transformed series of Mortality

3.1. Estimating the ARIMAX model

The ACF plot of the differenced series for the Deaths shown in Figure 2 revealed significant spikes at the non-seasonal lags 1, 3 and 56. Also, the PACF plot revealed that there were significant spikes at the non-seasonal lags 1, 3, 5 and 9.

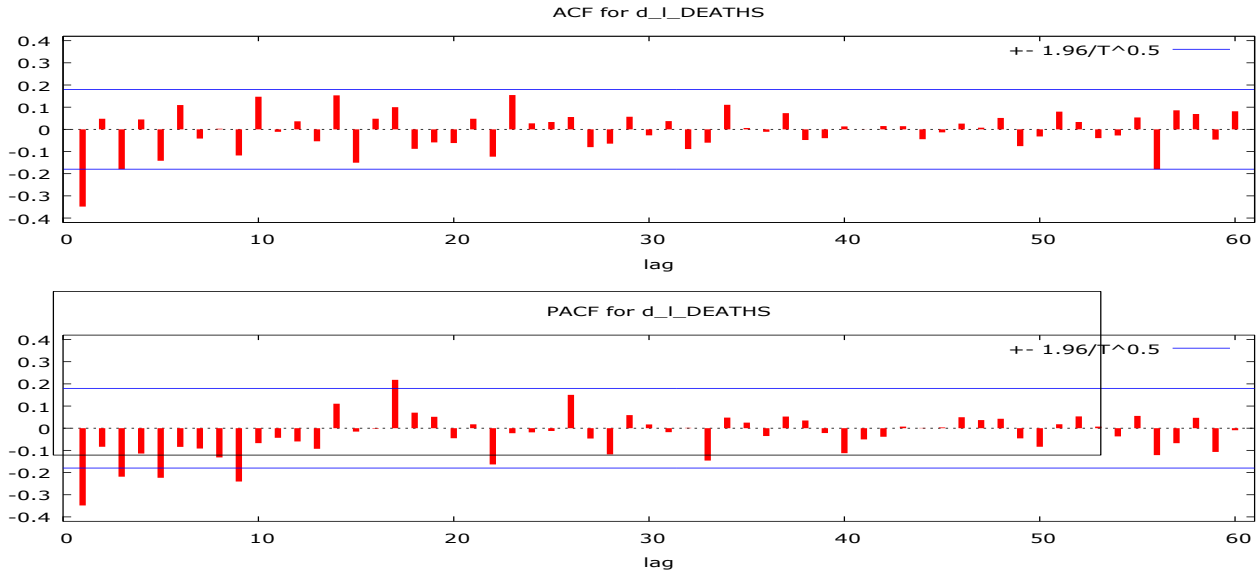

Figure 2: ACF and PACF plot of differenced series for Mortality

The lower significant lags of the ACF and PACF plots in Figure 3 were used to fit tentative ARIMAX models shown in Table 5. It was observed that ARIMAX (1, 1, 1) had the least AIC, AICc and BIC values and hence was considered as the best model.

Table 5: Tentative ARIMAX models

Model	AIC	AICc	BIC
ARIMAX (1, 1, 1)	171.4890*	171.5916*	179.8264*
ARIMAX (3, 1, 3)	175.2242	175.3268	194.6781
ARIMAX (3, 1, 1)	171.7322	171.8348	185.6279
ARIMAX (1, 1, 3)	173.0347	173.1373	186.9303

*: Means best based on the selection criteria

It was further observed from Table 6 that the *p*-values of the model parameters were both significantly high at the 5% level of significance. The model was therefore considered as the best compared to other models.

Table 6: Estimated parameters for ARIMAX (1, 1, 1)

Variable	Coefficient	Standard error	*z*-statistic	*P*-value
Dummy	-1.8809	0.0338	-0.2639	0.0072
ϕ	0.3629	0.1147	3.1637	0.0016
θ	0.8724	0.0619	-14.0957	0.0000

In terms of the backshift operator, the parameters of ARIMAX (1, 1, 1) shown in Table 7 can be expressed as:

$$\ln Mortalities = -1.8809D + \frac{(1 + 0.8724B)}{(1 - 0.3629B)(1 - B)}\varepsilon_t \qquad (15)$$

Where D= Dummy

In order to further buttress the selection of the model, a diagnostic test was carried out on the residuals of the model. It was observed from the diagnostic plot in Figure 4 that the standardised residuals of the model had a zero mean and constant variance. Again, the ACF plot of the model residuals revealed that all the residual autocorrelations were within the significance bounds implying that they were uncorrelated. Moreover, the Ljung-Box statistic clearly shows that the *p*-values of the test statistic exceed the 5% level of significance for all lag orders which implies that there is no significant departure from white noise for the residuals. The model is therefore considered as the best.

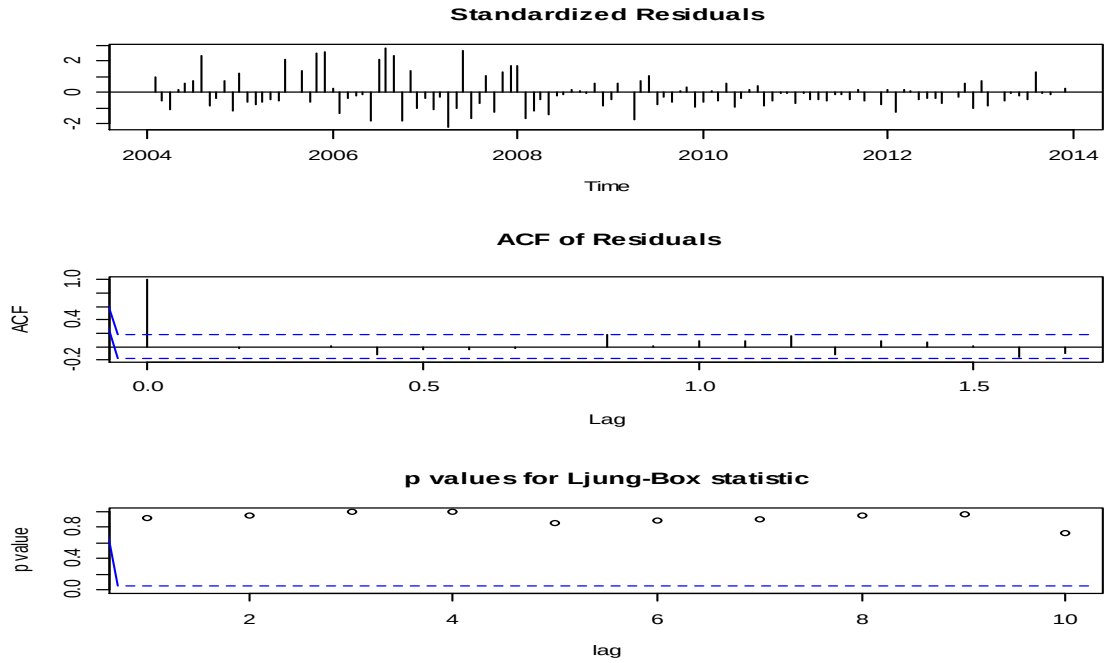

Figure 3: Diagnostic plot of ARIMAX (1, 1, 1)

An ARCH-LM test was conducted on the residuals of the model based on the assumption of constant variance and zero mean in order to confirm the information shown in Figure 3. Table 7 revealed that there was no ARCH effect in the residuals of the model. The Jarque-Bera normality test was also carried out and it was revealed that the residuals of the model were normally distributed. It was therefore concluded that the selected model, ARIMAX (1, 1, 1) is the best model since it satisfies all the diagnostic conditions.

Table 7: ARCH-LM test of residuals of ARIMAX (1, 1, 1)

Lag	Chi-squared	df	*P*-value
12	18.2315	12	0.7491
24	34.4269	24	0.9379
36	42.8077	36	0.9052

JB Test: Chi-squared= 12.3732, *p*-value=0.3124

Again, the CUSUM test was conducted in order to test the stability of the model parameters over time. From Figure 4, it was revealed that the cumulative residuals of the model fall within the 95% confidence band. Hence it can be concluded that the parameters of the model were structurally stable.

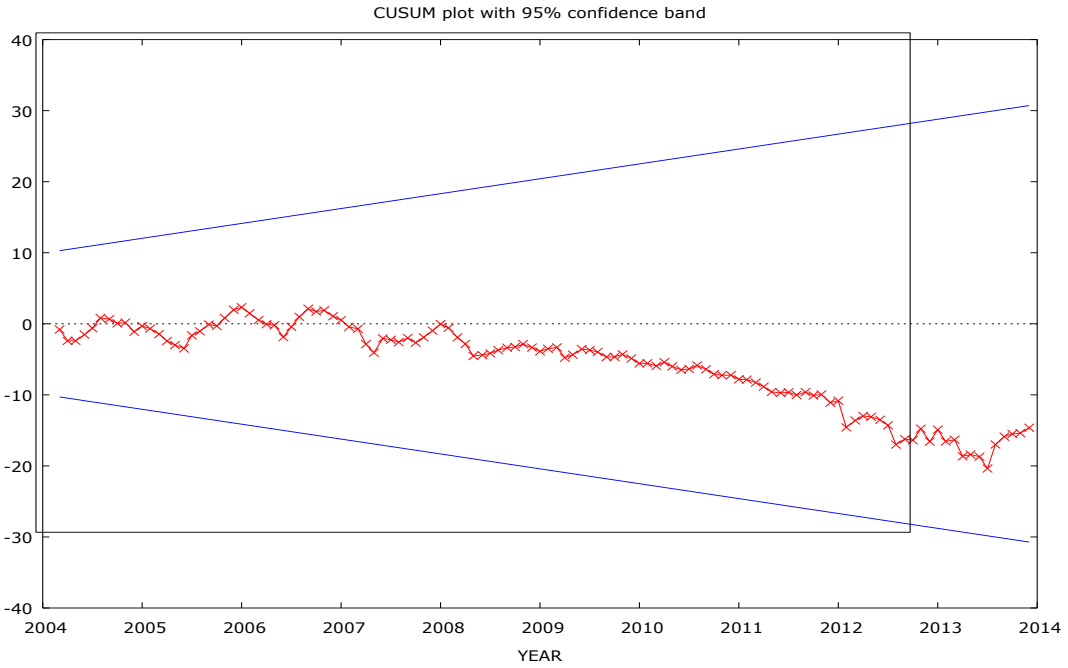

Figure 4: CUSUM plot of ARIMAX (1, 1, 1)

The model was cross validated by a chi-square goodness of fit test to determine whether there was a significant difference between the monthly expected numbers of Deaths and that of the observed for the year 2018. The test gave a chi-square calculated value of 10.35 and a critical value of 19.675 at 11 degrees of freedom and 5% significance level. We therefore fail to reject the null hypothesis of no significant difference between the observed and the expected values since the calculated value is less than the table value. It can therefore be concluded that there is no significant difference between the predicted values from the model and the observed values for the year 2018.

4. Conclusion

This study investigated the effects of malaria control interventions on mortality due to malaria in the Northern Region of Ghana. A model for predicting the number of deaths in the region was also determined. We observed that, the coefficient (-1.8809) of the intervention variable and p-value ($p<0.0072$) were negative and significant respectively, signifying a decrease in the number of mortalities for the period of the study. The decline in the number of mortality cases is an indication that the intervention was well implemented and its plans were also executed well. Based on the results, it is concluded that ARIMAX (1, 1, 1) is the best model for predicting the monthly number of mortality cases due to malaria in the region since the model had the least AIC, AICc and BIC. Diagnostic checks of the model with the Ljung-Box test and ARCH-LM test revealed that the model was free from higher-order serial correlation and conditional heteroscedasticity respectively. A steep decline in the number of cases recorded was observed from 2012 onwards. It is therefore recommended that the Government of Ghana through the National Malaria Control Programme (NMCP), other local and international agencies such as the AngloGold Ashanti Malaria Control Programme and the United States President's Malaria Initiative (PMI) should strengthen the current preventive measures (through indoor residual spraying, scale-up of the distribution of insecticide treated nets, intermittent preventive treatment for pregnant women, improving sanitation, increasing access to healthcare and improving data reporting) in order to maintain the steady decline in the number of cases. On the use of LLINs, follow ups should frequently be done to replace missing and worn out nets. The distribution of LLINs should be followed with mass education on the use and need to sleep under treated nets. Larviciding is a good measure used in the prevention of malaria which is practice only in the

southern part of the country. Hence it will not be out of place if conscious efforts are made to implement it in the north.

It is further recommended that this study be replicated in other regions of the country to help identify which regions are making progress in terms of reducing the malaria burden, so that more attention will be given to regions that still have a high incidence of malaria.

Acknowledgement

We would like to thank the management of the Northern Regional Health Directorate for providing us with the data to carry out this study.

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