

Research Article

Using Arima Model to Forecast Malaria Cases in Bolgatanga Municipality

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Abstract: This study was conducted with the aim of using ARIMA models to forecast malaria cases in the Bolgatanga municipality. The findings revealed that, the malaria cases are skewed to the right, indicating that most of the values are concentrated at the left of the mean and this means that majority of the cases are below the average indicating high complicated malaria cases in the municipality. Again, since the peakness demonstrated a platykurtic has a flattened than normal peak and this suggest that most of the malaria cases are spread to the extreme sides of the curve also exhibiting high complicated malaria cases in the municipality. The best model that described malaria cases in the municipality is the quadratic I model and ARIMA (0, 1, 0). The tests of best fit also confirmed that the final model was adequate for the forecast and the three years forecasted outcomes showed very steady increase in malaria cases over time. The suggested that the Municipal Health Workers should educate the populace how to prevent malaria and as well as distribute mosquito nets to the entire population of the municipality to reduce the projected likely increases in the malaria cases. World Health Organization and other Donald countries should come to the aid of the municipality to combat or eliminate vector completely. Government and Ministry of Health should formulate appropriate long-term policies such as if you deliberately refuse to sleep under treated mosquito-net and when caught you should be punish this would go a long way to prevent malaria cases completely in the municipality.

Keywords: Time Series Analysis, Linear trend model, Quadratic trend model, Autocorrelation Function, Partial Autocorrelation Function, Stationarity, Parameter Estimation, Parsimonious model and Differencing.

INTRODUCTION

Malaria is caused by the Plasmodium genus that is transmitted between humans by Anopheles mosquitoes (Thomas, 2014). *P. falciparum* and *P. vivax* are the most common species that cause malaria in humans. *P. falciparum* is the most dangerous because of the multi-drug resistance on this strain of the disease (Medical Research Council, 2001). A severe episode of cerebral malaria can result in epilepsy, cerebral palsy, or intellectual or physical disabilities (Davies & Eaton, 2018). These malaria victims are in the poorest, and sometimes most remote parts of the world, increasing the difficulty in finding support to cope with the disease (Davies & Eaton, 2018).

Malaria is both curable and preventable with medication therapy; however, a vaccine is not available. According to the World Health Organization, in 2012, there were approximately 207 million cases of malaria resulting in 627,000 deaths (World Health

Organization, 2014). The overwhelming majority that is 90% of these cases occur in Africa (Medical Research Council, 2001). Most of the deaths occur in children. However, the rate of deaths in children has been reduced by 54% since 2000 (World Health Organization, 2014). The Countries with the most confirmed cases are in sub-Saharan Africa and India. Moreover, malaria contributed to 2.05% to the total global death in 2000 and was responsible for 9% of all death in Africa (WHO, 2003). WHO also estimated that the total cost of treating malaria cases in Africa was US\$ 1.08 billion in 1995 and US\$2 billion in 1997 (WHO, 1997). Malaria is therefore a massive problem which plagues all segments of the society. It remains a major health challenge to mankind all over the world (World Health Organization, 2013). This is tied to the report that over three billion people in the world stand the risk of having malaria (World Health Organization, 2013). Despite local and international efforts towards the prevention of the disease, the rate

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at which people become sick and eventually die as a result of malaria is outrageous (Adebayo, Akinyemi, & Cadmus, 2015).

The future values of these variables are often predicted from their history. A time series analysis often does this and therefore this study was conducted to identify the trends of malaria cases in the Bolgatanga Municipality over the period 2009 to 2016 using time series analysis and to forecast future incidence for 2018, 2019 and 2020. A good way of describing the incidence of malaria is important and it will go a long way to ensure proper planning and evaluation in the implementation of programs to monitor and control the disease, especially in savanna zones.

Problem Statement

In Ghana, 3.5 million people contract malaria every year. Approximately 20,000 children die from malaria every year (25 per cent of the deaths of children under the age of five). Even if a child survives, the consequences from severe malaria such as convulsions or brain dysfunction can hamper long-term development and schooling. The annual economic burden of malaria is estimated at 1-2 percent of the Gross Domestic Product in Ghana. A malaria-stricken family spends an average of over one quarter of its income on malaria treatment, as well as paying prevention costs and suffering loss of income. Malaria-afflicted families on average can only harvest 40 percent of the crops harvested by healthy families. In endemic areas, as much as 60 percent of children's schooling may be impaired as a result of repeated bouts of malaria. Malaria endemic countries are among the worlds most impoverished. The cost of malaria control and treatment slows economic growth by about 1.3 per cent a year in Africa. Bolgatanga Municipality which is located in the Bolgatanga Municipality is known to have high crude death rate (CDR). The CDR of 9.1 of Bolgatanga Municipality is higher than the 6.2 for the Upper East Region of Ghana which is very alarming. With malaria being the leading cause of morbidity and mortality in the Municipality, it impedes economic growth and long term development of the Municipality. This is because it is the major cause of student and employee absenteeism and the decreased level of productivity that the Municipality continues to experience. With 64% of the population of the Municipality engaging in Agriculture where the most predominant crops millet, the extent of economic loss cannot be underestimated. This loss robs the country of some percentage of its Gross Domestic Product (GDP). The overall labor force is weakened by the disease, aside the pain, suffering and uncertainty associated with it. Poor families and people in the rural areas are mostly at higher risk due to lack of resources to seek proper treatment of the disease even in complicated and life threatening cases. Although Insecticide Treated Nets (ITN's) provide a cost effective means of ameliorating

the effects of malaria, this measure will be expensive if large human populations must be protected in the Municipality. Hence the need to analyze, monitor and predict the pattern of the disease in the Municipality, so as to come up with a measure to curb the spread of the disease.

Rationale of the Study

Malaria not only remains a leading cause of morbidity and mortality in the Bolgatanga Municipality, but it also impedes socioeconomic development, particularly in sub-Saharan Africa. Each year, there are approximately 515 million cases of malaria, killing between one to three million people, the majority of whom are young children (WHO, 2000). Malaria is commonly associated with poverty, but is also a cause of poverty and a major hindrance to economic development (Worrall, 2005). Malaria imposes substantial costs to both individuals and governments. Costs to individuals and their families include: purchase of drugs for treating malaria at home; expenses for travel to drug stores and treatment at, dispensaries and clinics; lost days of work; absence from school; expenses for preventive measures; expenses for burial in case of deaths. Costs to governments include: maintenance of health facilities; purchase of drugs and supplies; public health interventions against malaria, such as insecticide spraying or distribution of insecticide-treated bed nets; lost days of work with resulting loss of income; and lost opportunities for joint economic ventures and tourism.(RBM, 2005). This study aims to described the trend and pattern of malaria cases in the municipality in order to aid planning management of the disease.

The objectives of this study were:

- To determine the trend of malaria cases in the municipality using the Box - Jenkins (ARIMA) methodology.
- To develop an appropriate model that fit the malaria cases in the municipality.
- To make five forecast of malaria cases to aid planning and management of the disease.

Research Questions

- What is the trend of malaria cases in the municipality using the Box - Jenkins (ARIMA) methodology?
- Is there any appropriate model that fit the cases in the municipality?
- What are the five forecasts of malaria cases to aid planning and management of the disease?

Significance of the study

The potential implication of this study is that by developing forecasting models for predicting the expected number of malaria cases in advance, timely prevention and control measures can be effectively planned like eliminating vector breeding places, spraying insecticides, and creating public awareness.

The study will additionally enable policy makers and relevant stakeholders to foresee and allocate appropriate resources to maintain a steady increase of the spread of the disease.

LITERATURE REVIEW

Trend of malaria cases in Ghana

Malaria is a protozoan disease caused by parasites of the genus *Plasmodium*. It is one of the leading causes of illnesses and death in the world. It is the leading cause of death in children under the age of 5 years and pregnant women in developing countries (Martens and Hall, 2000). In 2010, there was an estimated 216 million cases of malaria worldwide, of which 91% were due to *Plasmodium falciparum*. The vast majority of cases (81%) were in the African Region followed by South-East Asia and, Eastern Mediterranean Regions by World Health Organization (WHO), (WHO, 2011). The disease remains the major causes of human morbidity and Corresponding author. Mortality with enormous medical, economic and emotional impact in the world.

Malaria has gained much recognition in Africa in recent years with the World Health Organization main target of eradication and therefore developing roadmaps in 2012 for prevention, control, and elimination (WHO, 2013).

Report by WHO indicates that malaria among the infectious diseases is attributed to about nine million deaths annually and it is one of the infectious disease of poverty (IDoP) believed to be prevalent among poorer communities (WHO, 2012). This shows that the association between poverty with lack of basic amenities and malaria is often interlinked. According to WHO, there are an estimated 35 million disability-adjusted life years (DALYs) attributed to malaria each year, (Laxminarayan and Ashford, 2008).

In Ghana, NMCP annual report, (2009) has indicated that malaria has been a major cause of poverty and low productivity accounting for about 32.5% of all out patients' attendance and 48.8% of admissions of children less than five years of age.

The attempt to control malaria in Ghana began in the 1950s. It was aimed at reducing the malaria disease burden till it no longer becomes public health significance. It was also recognized that malaria cannot be controlled by the health sector alone therefore; multiple strategies were being pursued with other health related sectors. In view of this, interventions were put in place to help in the control of the deadly disease. Some of the interventions applied at the time included residual insecticide application against adult mosquitoes, mass chemoprophylaxis with pyrimethamine medicated salt and improvement of drainage system. But malaria

continued to be the leading cause of morbidity (illness) in the country (NMCP, annual report, 2009).

Also, a report by the Government of Ghana Environmental Protection Agency assessment in 2006 indicated that, malaria continues to be the leading cause of outpatient attendance and admissions in all health facilities, accounting for about 44.1 percent of outpatient attendance in 2004 (Government of Ghana Environment Protection Agency assessment report, 2006).

As cited in Ministry of Health's (MOH) Revised Anti- Malaria Drug Policy for Ghana, (2009), Ghana committed itself to the Roll Back Malaria (RBM) initiative in 1999 and developed a strategic framework to guide its implementation. Overall, the Ghana RBM emphasizes the strengthening of health services through multi and inter-sectorial partnerships and making treatment and prevention strategies more widely available. The goal was to reduce malaria specific morbidity and mortality by 50% by the year 2010, (MOH, Revised Anti-Malaria Drug Policy for Ghana, 2009). Though Ghana has been making progress in implementing its NMCP, there are yet some lapses in achieving the targets. Ghana implemented a malaria control programme with a goal that generally aimed at reducing death and illness due to the malaria diseases by 75% by the year 2015 in line with the attainment of the Millennium Development Goals (MDGs). This goal was to be achieved through overall health sector development, improved strategic investments in malaria control, and increased coverage towards universal access to malaria treatment and prevention interventions.

According to the Ghana Health Service, (2008), nearly one-third of all deaths in children under 5 were due to malaria. The use of long-lasting insecticide-treated bed nets (LLINs) is believed to be one of the best ways to prevent this illness at the community level (MOH, Revised Anti-Malaria Drug Policy for Ghana, 2009).

The study seeks to investigate the trends of malaria cases in Ghana from 1985 - 2008.

RESEARCH METHODS

The study made use of monthly malaria cases report for the Bolgatanga municipality. The data was obtained from Regional Health Directorate Health. The data covered periods from January 2009 to December 2016. Malaria incidence in Bolgatanga municipality was forecasted using autoregressive integrated moving average (ARIMA) models in order to build a predictive tool for malaria surveillance. The order of non-seasonal model represented by

ARIMA (p,d,q) describes autocorrelation over a maximum order of p months; differencing order of d

adjacent months and moving averages process order of q months. The Box and Jenkins approach was used to determine the patterns best describing the malaria time series. Malaria incidence time plot was made to detect and fix issues of non-stationarity. After achieving stationarity, models of varying orders were fitted, and compared using normalized Bayesian information criterion (BIC), mean absolute error (MAE), and Stationary-R Square. Autocorrelation function (ACF) which evaluates the correlation between the time series data and Partial autocorrelation function (PACF) which shows the correlation between the autoregressive time lags were used to determine the parameters of the ARIMA model. The correlation values fell within the confidence limit which was set for the ACF and PACF; an indication of acceptable forecasting ability. ACF and PACF graphs of normalized data were used in the determination of the parameters p and q of the ARIMA model. Trial and error method was used to determine the final structure of the forecasting model. The model with the least BIC, AIC, HQ and the highest Stationary-R Square was selected for forecasting purpose. Data analysis was performed using minitab, gretl and R-programme (Bosson-Amedenu, 2017).

Time series

To understand the elements in a time series, the analyst must consider the mathematical relationships among the various components. The most widely used model for time series decomposition is the multiplicative model, in which the series is analyzed as the product of its components. The model is:

$$Y = T \times C \times S \times I$$

Where

Y = Actual value of the variable of interest

T = Secular trend

C = Cyclical component

S = Seasonal component

I = Irregular component

In the equation, Y is the product of four elements acting in combination to produce the series. The secular trend is the long-term component that represents the growth or decline in the time series over an extended period of time. The cyclical component is the wavelike fluctuation around the trend. The seasonal component is a pattern of change in quarterly or monthly data that repeats itself from year to year. The irregular component is a measure of the variability of the time series after the other components have been removed. (Bosson-Amedenu, 2017)

An approach widely known as the Box-Jenkins methodology uses both the autoregressive and moving average techniques for forecasting. This methodology does not assume the presence of a particular pattern in the historical data of the series to be forecast. Instead, the Box-Jenkins technique, credited to George Box and Gwilym Jenkins, uses an iterative approach of identifying a potentially useful model from a general

class of models. The selected model is then checked against the historical data to see if it accurately predicts the series. The model fits well if the residuals between the forecast value and the historical data points are small, randomly distributed independent. If the specified model is not satisfactory, the process is repeated using another model designed to improve on the original one. This process is repeated until a satisfactory model is found. Once a series has been identified as being stationary, the appropriate form of the ARIMA model is identified through examination of a correlogram containing the sample autocorrelation coefficients. (Bosson-Amedenu, 2017)

Sample partial autocorrelation coefficients are also a computer program used to identify the appropriate ARIMA model. Once the model has been selected, a computer program uses a nonlinear least squares procedure to estimate the model coefficients. As a final step in the model selection process, diagnostic checking of the residuals takes place to determine whether the model is appropriate. This is accomplished through examination of a correlogram containing the sample autocorrelations of the residuals. If none of the autocorrelations is significantly different from zero, it is assumed that the sample residuals are independent with mean 0, and the model is deemed adequate. The Box-Jenkins methodology is a very powerful tool for providing accurate short-range forecasts. However, it is quite complex, requiring extensive computer analyses to perform the numerous computations required for identifying the model, estimating the parameters, and verifying that the model is adequate. To build a satisfactory model requires a great investment in terms of the analyst's time and computer resources. Also, analyst should always remember that the more complicated the forecasting model, the less likely its results are to be understood and accepted by management and used in the decision-making process (Bosson-Amedenu, 2017).

RESULTS AND ANALYSIS

Exploratory data analysis

An exploratory data analysis on students' enrolment for the fifteen consecutive year period using mainly Minitab software, R programme and Gretl software, and the Box-Jenkins methodology of time series analysis was also employed. Some computations were made to first obtain the descriptive statistics in relation to the malaria cases, followed by time series plots and a trend analysis.

Table 4.1: Descriptive Statistics of malaria cases in bolgatanga municipality

<i>Malaria Cases</i>	
Mean	3975.268519
Standard Error	261.4509371
Median	3523.5
Mode	9
Standard Deviation	2717.077841
Sample Variance	7382511.993
Kurtosis	1.22205777
Skewness	0.956629338
Range	13857
Minimum	0
Maximum	13857
Sum	429329
Count	108
Confidence Level (95.0%)	518.2959899

The minimum value in the data set was found to be 0 and maximum 1385 whilst the average malaria cases was 3975.268519 with accompanying standard deviation of 2717.077841, indicating that the data is widely dispersed across the mean. The coefficient of variation of 21.5% also shows that the data has a very high variance. The malaria cases distribution also exhibits positive skewness of 0.956629338 indicating that most of the cases are concentrated to the left of the mean and also has a kurtosis value of 1.2221 also indicating that the data is platykurtic, thus, has a flattened than normal peak.

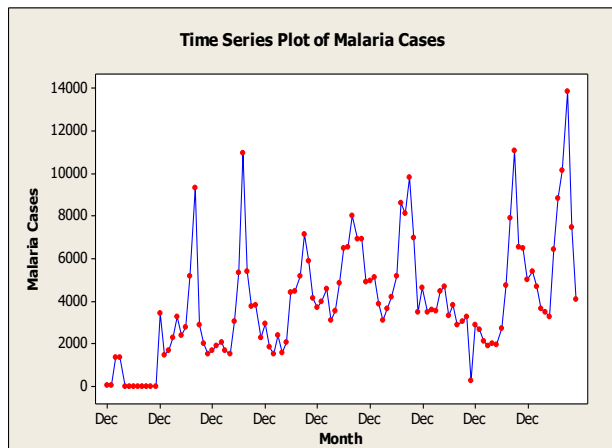


Figure 4.1: time series plot of malaria cases in Bolgatanga municipality

The plot in Figure 4.1 shows the fluctuation pattern of malaria cases with respect to time. It can be observed, generally, from the figure that increasing trend in the plot is significantly sharp. Malaria cases however, took a significant upward and trend over the time downward respectively. The generally increasing pattern in the time graph shows a gradual change of the mean whilst the flattened fluctuations over time shows an unstable variance suggesting the series is not stationary.

Table 4.3 STATIONARY TEST

TEST	TEST STATISTIC	P-VALUE
KPSS	0.105058	0.148
ADF	0.148877	0.7293

From the KPSS test values on table 4.2, at 5% significance level, the conclusion is that the series is stationary since the p-value (0.148) is greater than 0.05. However, the ADF test with a reverse null hypothesis indicates that the data is not stationary with p-value 0.7293. In all, the data is concluded to be non-stationary based on the evidence of the time plot, correlogram and KPSS test, hence needed to be difference.

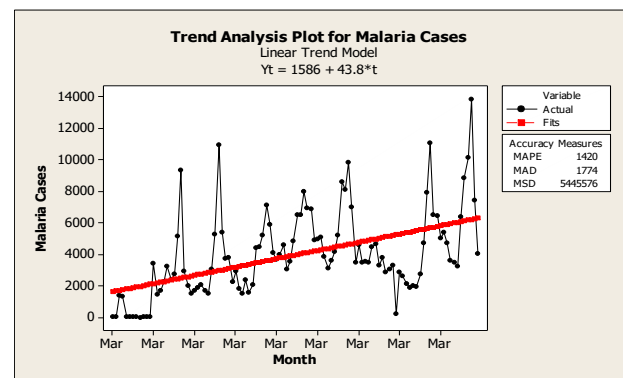


Figure 4.2: trend plot of malaria cases in Bolgatanga municipality

Figures 4.2 and 4.3 below show the linear and quadratic models respectively. In each of the figures, round dotted lines represent the actual values of malaria cases whereas the square dotted lines represent the fitted values based on the various models

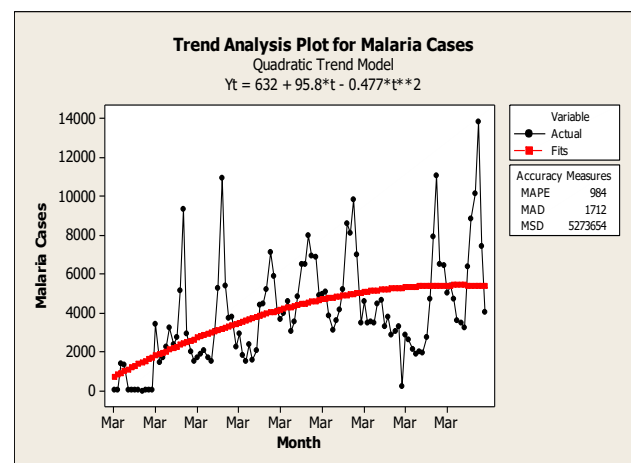


Figure 4.3: Quadratic trend plot malaria cases in Bolgatanga municipality

Table 4.3: Measures of accuracy

Model	MAPE	MAD	MSD
Linear	1420	1774	5445576
Quadratic	984	1712	5273654

From **Table 4.3** the most appropriate model to describe the trend in malaria cases in Bolgatanga municipality is the one with minimal errors. A closed observation of the errors produced by two models, the quadratic model has the minimum MAPE, MAD and thus, is considered to be the best model in describing the trend in malaria cases in Bolgatanga municipality.

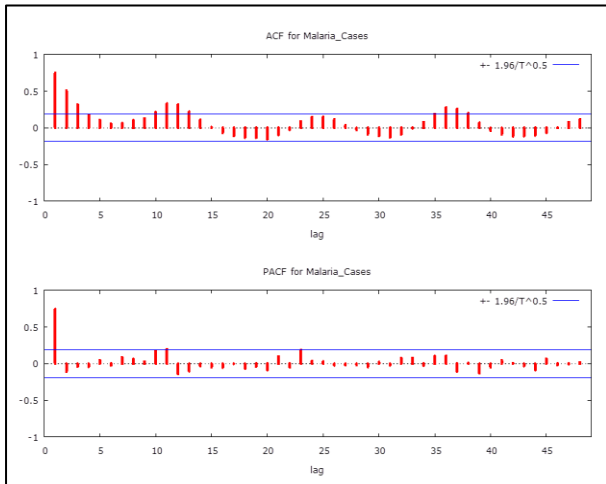


Figure 4.4: ACF and PACF of malaria cases

Further analysis was conducted and checks made on the Autocorrelation Function (ACF) plots and those of the Partial Autocorrelation Function (PACF). It can be observed that with 95% confidence interval the data appears not stationary. The ACF is dying down slowly with significant spikes at lags 1, 2 and 3 of the PACF as illustrated in Figures 4.4

Tests for Stationary

A stationary process has a mean and variance that do not change over time and the process does not have trends. To proceed with the estimation of an ARIMA model, the series is required to be stationary, as such this study employed the Augmented Dickey-Fuller (ADF) test and the

Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test for evidence of stationarity in malaria cases in quantitative methods.

Augmented Dickey-Fuller Test

For the ADF test, we test the hypothesis that;
 H0: the series is not stationary.
 H1: the series is stationary.

At 95% significance level, a p-value less than 0.05 means a rejection of H0, meaning the series is stationary, otherwise the H0 is upheld.

Kwiatkowski, Phillips, Schmidt and Shin Test

The KPSS test has a reverse hypothesis to the ADF test hence;

H0: the series is stationary.
 H1: the series is not stationary.

This means that at 95% significance level, a p-value less than 0.05 means we reject H0 and say the series is not stationary, otherwise it is stationary.

Achieving Stationary

As a result of the *not stationary* nature of the data, there was the need for it to be differenced in order to obtain stationary before building any model. Since the series has an exponential growth trend and increasing variance over time it was necessary to transform the data by taking the logarithm of the series and then difference it. A time plot of the transformed data is examined and tested for stationary.

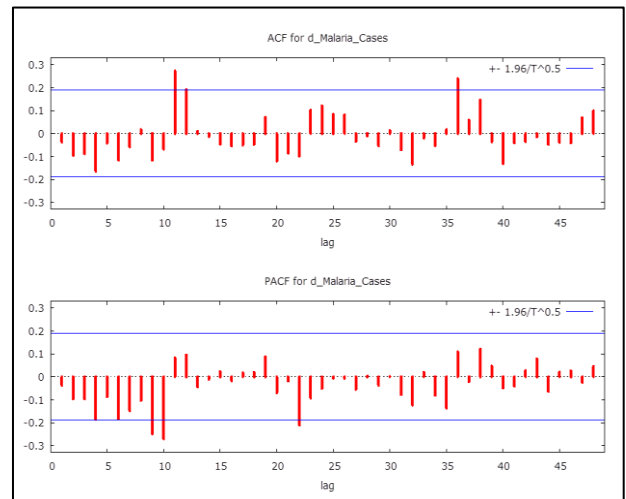


Figure 4.5: Time Series Plot of Differenced malaria cases

Figure 4.5 shows the correlogram of the differenced malaria cases data. It shows a rapid decay indicating stationary. The stationary of the differenced data however, must be confirmed by performing the ADF test and the KPSS test once again. The results in Table 4.4 below show that both tests confirm stationary after first differencing

Table 4.4 STATIONARY TEST

TEST	TEST STATISTIC	P-VALUE
KPSS	0.0530132	0.148
ADF	-2.93095	0.003291

The Box-Jenkins Method of Modelling Time Series

The Box-Jenkins methodology (Box & Jenkins, 1976) is a step-wise statistical method used in analyzing and building forecasting models which best represents a time series. This method of forecasting implements knowledge of autocorrelation analysis based on autoregressive integrated moving average models. The methodology makes great use of historical time series data, is logically and statistically accurate and increase forecasting accuracy. The procedure is of four distinct stages namely; Identification, Estimation, Diagnostic checking, Forecasting.

Model identification

Table 4.5: model identification

Model	AIC	BIC	HQ
Arima(0,1,0)	1922.390	1925.063	1923.474
Arima(0,1,1)	1926.191	1934.209	1929.441
Arima(0,1,2)	1922.882	1933.573	1927.216

The most appropriate model for the series is the one with the minimum Akaike Information Criteria (AIC), Bayesian information criterion (BIC) and Hannan-Quinn (HQ). Thus, by an inspection of all the competing models in table 4.5 the ARIMA (0, 1, 0) model has the minimum values and therefore the best model for forecasting.

Parameter Estimation

Table 4.6 below displays estimates of the parameters of the ARIMA (0, 1, 0) model. The parameters of both MA (0) and AR(0) are significant at 5% levels with coefficients and p-values of and respectively. less than 0.05 indicates the significance of the parameters.

Table 4.6: Parameter Estimates for ARIMA (0, 1, 0)

Type	Coefficient	Standard error	Z value	P-value
Const	37.9346	185.514	0.2045	0.8380

Model Diagnosis

To ensure that the selected model is the best model that suits the data the following diagnostics are Performed.

Residuals Plots

The patterns of the residuals over time around the zero mean as seen in figure 4.8 below indicates that the residuals are random and independent of each other, thus, indicating that the model is fit.

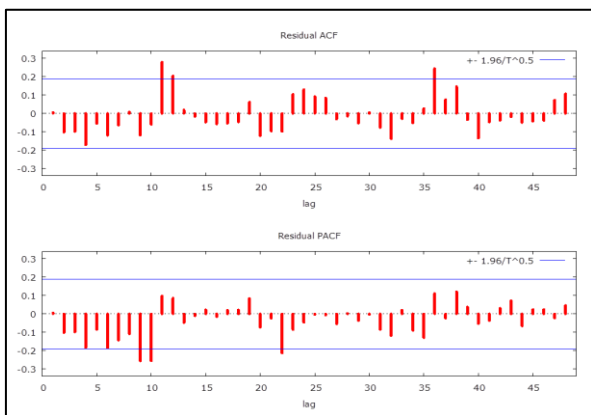


Figure 4.8: residual plot of ACF and PACF

Figure 4.8 shows all autocorrelation spikes within the 95% confidence interval. This means that

there is no serial correlation between residuals indicating that they are accurate and the model is adequate.

The Normal Q-Q Plot

The Normal Q-Q Plot is another diagnostic check on the residuals to determine whether it follows the normal distribution. This is done by using the normal probability plot (Q-Q plot). It is a plot a plot based on estimates of the quantiles. The normal Q-Q plots is used to compare the distribution of a sample to a theoretical distribution. If most of the points are in line and closer to the normal line, then the model is a good fit.

The Q-Q plot in Figure 4.9 below shows all points along the normality line except for one outlier hence the model is deemed fit.

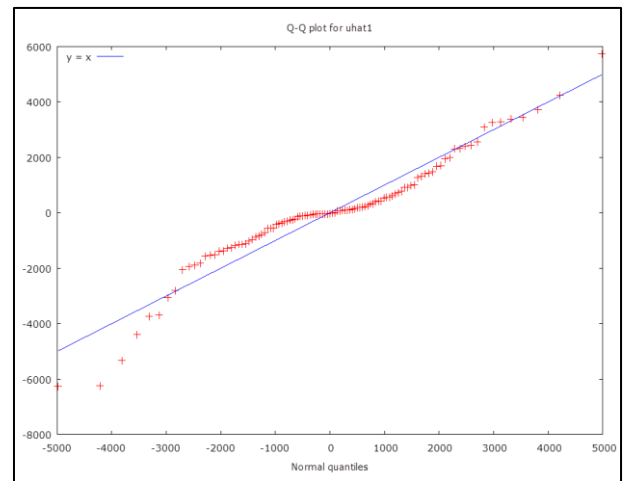


Figure 4.9

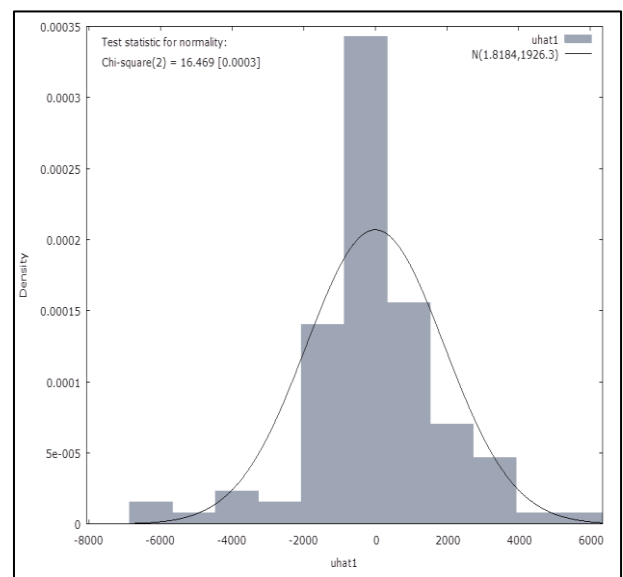


Figure 4.10

Ljung-Box Q Statistics

A check of the overall model adequacy is made using the Ljung-Box Q statistics. With a p-value of 0.834 which is way greater than 0.05 indicates that the model is generally adequate.

Table 4.7 Ljung-Box Q Statistics

MODEL	Statistics	DF	Sig.
Arima(0,1,0)	5.8	10	0.834

FORECAST

Since the model checks out to be of good fit, we can now forecast for future values in this instance, the next 5 observations

Malaria_Cases	prediction	std. error	95% interval
2017:01	4300.42	1908.176	560.47 - 8040.38
2017:02	4338.36	2632.463	-821.17 - 9497.90
2017:03	4376.30	3196.652	-1889.02 - 10641.63
2017:04	4414.24	3675.229	-2789.07 - 11617.56
2017:05	4452.18	4098.296	-3580.33 - 12484.70
2017:06	4490.12	4481.602	-4293.66 - 13273.90
2017:07	4528.06	4834.613	-4947.60 - 14003.73
2017:08	4566.00	5163.546	-5554.36 - 14686.37
2017:09	4603.94	5472.744	-6122.44 - 15330.33
2017:10	4641.88	5765.384	-6658.06 - 15941.83
2017:11	4679.82	6043.871	-7165.95 - 16525.59
2017:12	4717.76	6310.080	-7649.77 - 17085.29
2018:01	4755.70	6565.503	-8112.45 - 17623.85
2018:02	4793.64	6811.355	-8556.37 - 18143.65
2018:03	4831.58	7048.637	-8983.49 - 18646.66
2018:04	4869.52	7278.187	-9395.46 - 19134.51
2018:05	4907.46	7500.715	-9793.67 - 19608.59
2018:06	4945.40	7716.829	-10179.30 - 20070.11
2018:07	4983.34	7927.053	-10553.40 - 20520.08
2018:08	5021.28	8131.845	-10916.84 - 20959.41
2018:09	5059.22	8331.604	-11270.42 - 21388.87
2018:10	5097.16	8526.685	-11614.83 - 21809.16
2018:11	5135.10	8717.401	-11950.69 - 22220.89
2018:12	5173.04	8904.033	-12278.54 - 22624.63
2019:01	5210.98	9086.832	-12598.88 - 23020.85
2019:02	5248.92	9266.027	-12912.16 - 23410.00
2019:03	5286.86	9441.820	-13218.77 - 23792.49
2019:04	5324.80	9614.400	-13519.08 - 24168.68
2019:05	5362.74	9783.937	-13813.42 - 24538.91
2019:06	5400.68	9950.585	-14102.11 - 24903.47
2019:07	5438.62	10114.488	-14385.41 - 25262.66
2019:08	5476.56	10275.777	-14663.59 - 25616.72
2019:09	5514.50	10434.573	-14936.89 - 25965.89
2019:10	5552.44	10590.989	-15205.51 - 26310.40
2019:11	5590.38	10745.128	-15469.68 - 26650.45
2019:12	5628.32	10897.086	-15729.57 - 26986.22
2020:01	5666.26	11046.955	-15985.37 - 27317.90
2020:02	5704.20	11194.818	-16237.24 - 27645.64
2020:03	5742.14	11340.752	-16485.32 - 27969.61
2020:04	5780.08	11484.833	-16729.78 - 28289.94
2020:05	5818.02	11627.128	-16970.73 - 28606.78
2020:06	5855.96	11767.703	-17208.31 - 28920.24
2020:07	5893.90	11906.619	-17442.64 - 29230.45
2020:08	5931.84	12043.932	-17673.83 - 29537.51
2020:09	5969.78	12179.697	-17901.99 - 29841.55
2020:10	6007.72	12313.965	-18127.21 - 30142.65
2020:11	6045.66	12446.785	-18349.59 - 30440.91
2020:12	6083.60	12578.203	-18569.22 - 30736.43

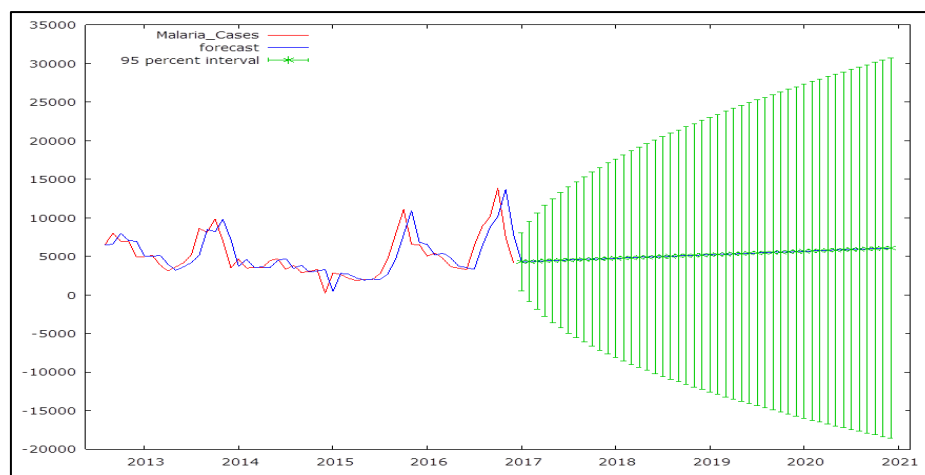


Figure 4.11: The graph for the five-year forecasted model of malaria cases

From figure 4.11, it is can be observed that malaria cases will experienced steady increases in the municipality as indicated on figure 4.10 range of 2019-2021.

DISCUSSIONS OF RESULTS AND CONCLUSION

From the descriptive statistics, in Table 3.2 it is observed that malaria cases are skewed to the right, indicating that most of the values are concentrated at the left of the mean and this means that majority of the cases are below the average indicating high complicated malaria cases in the municipality. Again, since the peakness demonstrated a platykurtic has a flattened than normal peak and this suggest that most of the malaria cases are spread to the extreme sides of the curve also exhibiting high complicated malaria cases in the municipality

Figure 4.1 shows an upward and downward trend with high and low peak indicating an irregular or random trend with the series showing a generally increasing trend. The generally increasing pattern in the time graph shows a gradual change of the mean whilst the flattened fluctuations over time shows an unstable variance suggesting the series is not stationary. Figure 4.2- Figure 4.3 describe various trend models of the series and the best trend descriptor per the measures of accuracy in Table 4.3 is the quadratic 1 model. Secondly, even though the data was transformed by way of differencing to achieve stationarity and the tests of best fit also confirmed that the final model was adequate for the forecast, the three years forecasted outcomes showed very steady increase in malaria cases over time. Thus, further demonstrating that malaria cases are likely to received steady increases in the future if the government non-governmental organization, developed country and world health organization do not introduce innovations methods of either preventing or complete elimination of the disease.

Recommendations/Suggestions

Based on the findings of this study, couples with the fact that Bolgatanga municipality is located in the savanna zones the study, commends/suggests the following:

- The Municipal Health Workers should educate the populace how to prevent malaria and as well as distribute mosquito nets to the entire population of the municipality to reduce the projected likely increases in the malaria cases.
- World Health Organization and other Donald countries should come to the aid of the municipality to combat or eliminate vector completely.
- Government and Ministry of Health should formulate appropriate long-term policies such as if you deliberately refuse to sleep under treated mosquito-net and when caught you should be punish this would go a long way to prevent malaria cases completely in the municipality
- Disease Control Officers should be deploy to all the sub-communities to educate the populaces about consequences of not sleeping under treated mosquito-nets.
- Both Governmental and Non-Governmental Organizations should support the municipality by donating mosquito-nets to help reduce the malaria cases.
- Disease Control Officers and Community Health Nurses should pay regular visit to communities to check on the populaces whether they sleep under the treated mosquito-nets that has been distributed.

REFERENCES

1. Adebayo, A. M., Akinyemi, O. O., & Cadmus, E. O. (2015). Knowledge of malaria prevention among pregnant women and female caregivers of under-five children in rural southwest Nigeria. *PeerJ*, 3, e792.
2. Davies, M., & Eaton, J. (2018). *Malaria: Finding a preventive strategy that African countries can afford*. The Guardian.
3. Ghana Health Service. (2008). Annual Report

4. Ghana malaria programme review final report. (2013). Ghana Health Service.
5. Laxminarayan, R., & Ashford, L. (2008). Using evidence about “best buys” to advance global health. In Policy Brief: Disease Control Priorities Project. 2008. Malaria_Info.pdf
6. Medical Research Council. (2001). *Malaria advice for southern Mozambique, Swaziland, and South Africa*. Retrieved from http://www.malaria.org.za/Malaria_Risk/riskadv/General_
7. NMCP annual report. (2009). National Malaria Control Programme, annual report.
8. Thomas, L. O. (2014). A comprehensive review of malaria with an emphasis on plasmodium resistance (Diss.). University of Mississippi.
9. World Health Organization. (2013). World malaria report. Geneva, Switzerland
10. World Health Organization. (1997). *Application of the international classification of diseases to neurology: ICDNA*. World Health Organization.
11. World Health Organization. (2003). *WHO technical report series No. 892*. Geneva: WHO Expert Committee on Malaria.
12. World Health Organization. (2013). *Fact sheet on the world malaria report 2013*. Retrieved from http://www.who.int/malaria/media/world_malaria_report_2013/en/
13. World Health Organization. (2014). *Malaria* [Internet]. Retrieved from <http://www.who.int/mediacentre/factsheets/fs094/en/>
14. World Health Organization. (2012). WHO Global Malaria Programme: World Malaria Report. Switzerland: Available at http://www.who.int/malaria/publications/world_malaria_report_2012/report/en/.
15. World Health Organization. (2011). World malaria report. Geneva, Switzerland.