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Master Program in Statistics and Information Management

# Time Series Analysis on Rate of Malaria and Typhoid Fever: Case Study Nigeria (2003-2017)

Nwakuwa Esther Promise

Dissertation presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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by

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**Supervisor:** Professor Jorge Morais Mendes

JULY 2020

# DEDICATION

This master thesis is dedicated solely onto my Lord Jesus Christ, who mercy is new every day.

# ACKNOWLEDGEMENTS

First and foremost, I want to give my sincere gratitude to my mother Mr /Mrs Nwakuwa with a deep sense of appreciation, I would like to thank the NOVA Information Management School, Universidad Nova de Lisboan, Portugal. The faculty of lectures, my heritage course mates who guided me and contributed so thoroughly through their emails, recommendations, comments on this thesis and the entire Statistics Department and the Information Technology Department for their willingness to impart their knowledge throughout the duration of the postgraduate Diploma course that led the master's degree.

Further, I would like to thank my thesis supervisor professor Jorge Mendes for your devotion, erudite guidance, love, patience, assistance, accommodating and your advice.

Lastly, I cannot forget to thank my family, well-wishers, and friends for all their support during my master's degree academic years, I truly appreciate you.

# ABSTRACT

Malaria and typhoid fever are major causes of death in Sub-Saharan African countries. Due to the high risk of these two diseases in Sub-Saharan African countries and Nigeria in particular, this dissertation investigate the incidence of malaria and typhoid fever in Nigeria from January 2003 to December 2017 with the aim of identifying an appropriate statistical model that can be used to describe the trend of malaria and typhoid fever and make future projections of the two diseases in Nigeria which will serve as guide to policy makers in reducing the incidence of the two diseases.

Several statistical methods were used in this research work. The Least Square Estimation was used to estimate the trend of both malaria and typhoid fever and the trend line equation obtained shows a gradual downward trend movement for both diseases. Arima modeling was used to describe the general behavior and pattern of occurrence of both diseases over the period under study and forecasts of future occurrence were made. SARIMA model was identified as the appropriate model for both malaria and typhoid fever. This result shows that the incidence of both diseases is influenced by seasonal factor. High occurrence of both diseases is expected around May to August according to the forecasts obtained in this study. The Chi-square test of association was used to ascertain if any form of association exists between gender and the diseases and the result obtained shows that there is no significant association between gender and the diseases. Correlation analysis conducted shows that there is a strong relationship between the two diseases.



# Keywords

Malaria; Typhoid fever; Diseases; Probability; ARIMA

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# LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| **ACF** | Autocorrelation Function |
| **ACT** | Artemisinin-based Combination Therapy |
| **ADF** | Augmented Dickey Fuller |
| **AIC** | Akaike Information Criteria |
| **AIDS** | Acquired Immunodeficiency Syndrome |
| **AR** | Auto-regressive |
| **ARIMA** | Auto-regressive Integrated Moving Average |
| **ARMA** | Auto-regressive Moving Average |
| **BIC** | Bayesian Information Criteria |
| **DF** | Degree of Freedom |
| **DHIMS** | District Health Information Management System |
| **DRC** | Democratic Republic of Congo |
| **EDA** | Exploratory Data Analysis |
| **HIV** | Human Immunodeficiency Virus |
| **ITNs** | Insecticide Treated Nets |
| **LGAs** | Local Government Areas |
| **LSE** | Least Square Estimation |
| **MA** | Moving Average |
| **MAWSH** | Muhammad Abdullahi Wase Specialist Hospital |
| **PACF** | Partial Autocorrelation Function |
| **SARIMA** | Seasonal Auto-regressive Integrated Moving Average |
| **SE** | Standard Error |
| **SP** | Sulfadoxine-pyrimethamine |
| **WHO** | World Health Organization |

# CHAPTER ONE
# INTRODUCTION

## 1.1 BACKGROUND OF THE STUDY

Malaria and typhoid fever are major public health problems in tropical and subtropical countries of Africa with people in endemic areas having higher risk of contracting both infections concurrently, (Birhanie et al., 2014). These two diseases are life-threatening diseases caused by the protozoan Plasmodium and the bacterium Salmonella typi, respectively (Iwuafor et al., 2016). Malaria is a disease contacted through the bite of an infected mosquitoes (Obimakinde and Simon-Oke, 2017) while typhoid fever is contacted through contaminated food or water. Malaria affects half of the world's population with 3.3 billion people affected in 106 countries (Nigeria Malaria Fact Sheet (2011)). In Nigeria, there are over 300,000 deaths per year from estimated 100 million cases of malaria while there are 215,000 deaths per year from HIV/AIDs (Nigeria Malaria Fact Sheet, 2011). As alarming these statistics could be, the awareness of the threat posed by these diseases is considerably low in developing and underdeveloped nations unlike awareness given to HIV and aids infections. In particular, the rural areas of such nations face the largest challenges of prevention and treatment. This study tends to study the pattern of malaria and typhoid fever in Nigeria with a view to provide future occurrence of these diseases for desicive measures by relevant authorities. In recent time, both malaria and typhoid fever have been classified as an epidemic in Africa due to their high incidence, since the two diseases affect a greater proportion of the African population (Gillet et al., 2010). Out of the 216 million cases of malaria recorded globally, approximately 175 million cases were recorded in Africa (Nigeria Malaria Fact Sheet, 2011). In 2004, it was estimated that 22 million new cases of typhoid fever occur each year globally with approximately 200,000 deaths from typhoid fever (Crump et al., 2004). Nigeria and some other African countries like Democratic Republic of Congo (DRC), Ethiopia, and Uganda contributes almost half of the deaths caused by malaria globally (Nigeria Malaria Fact Sheet, 2011). Despite the National health policy in Nigeria that Artemisinin-based combination therapy (ACT) should be used as the first-line treatment of uncomplicated malaria, it was reported in 2010 that over 70% of children treated for malaria in Nigeria received chloroquine or sulfadoxine-pyrimethamine (SP) (Nigeria Malaria Fact Sheet, 2011). These diseases are widespread in rural and urban areas of Nigeria, where the tropical nature of this geographical location has promoted a persistent increase in cases of malaria and typhoid fever. This epidemic mainly affects Sub-Saharan African countries such as Nigeria and has been a major health problem that needs urgent attention.

Both malaria and typhoid fever have similar epidemiology symptomology. Specifically, malaria and typhoid fever are transmitted through the bite of female Anopheles mosquitoes, which thrive in the presence of dirty water (stagnant water), poor sanitation and contaminated food(Odikamnoro et al., 2018). Malaria is one of the febrile illnesses and the most common fatal disease in the world caused by

one or more species of plasmodium. These are plasmodium falciparum, Typhoid fever (enteric fever) is a systematic prolonged febrile illness caused by certain salmonella genotypes.

The survival rate of both malaria and typhoid fever is considerably low, especially in the rural areas. Awareness of the danger of malaria and typhoid fever among the populace is low because many see these diseases as a situation that can be managed without the help of a specialist or medical practitioner. The alarming incidence of malaria and typhoid fever calls for urgent research in the area for possible intervention. In 2013 WHO reported that the case rate and mortality rate for both diseases since 2000 is 30% and 40% respectively. Infants, children and adolescents in Nigeria are among those most affected by this illness. These diseases share the same symptom which are of vital to the transmission(Odikamnoro et al., 2018). The fact that malaria and typhoid fever share the same symptomology makes these diseases hard to diagnose. Thus, the importance of definitive laboratory, based diagnosis cannot be overemphasized. In particular, the presence of Plasmodium and Salmonella typhi must be confirmed before an individual is diagnosed with malaria or typhoid fever, respectively (Uneke, 2008).

This research project is set out to show-case the threat posed by malaria and typhoid fever in developing nations of Sub-Saharan Africa, using Nigeria as a case study. Specific attention will be paid to data from 2003 to 2017 to determine the trend for the occurrence of these diseases. Different statistical methodologies will be employed to assess the trend and behavior of both diseases with the aim of understanding the pattern of evolvement of both disease over the years and to make projections for future occurrence of both diseases which may serve as a guide to government for future planning. Also, the co-infection of both diseases will be assessed to determine the chances of contacting one disease from the other.

## 1.2 Problem Justification

Among the factors that lead to shifts in population size are birth, migration, and death. Death is an important factor that can lead to a significant reduction in the population size of a nation.

In developed nations, the standard of living and access to health facilities have made life easy for the populace. In developing and under-developed nations, however, access to basic health care facilities is considerably low which leads to lower life expectancy among the people. Several common diseases that can easily be treated do cause death in such locations due to ignorance and lack of basic health care facilities.

Among the diseases or causes of death in developing and under-developed nations is malaria and typhoid fever, which are triggered by poor living conditions especially among the low-income earners. Most of the treatments done in the hospitals among infants and adults have to do with malaria and typhoid fever. The danger posed by these diseases is not well known by many in the region due to ignorance or lack of exposure.

This research project aims to investigate the incidence of malaria and typhoid fever in Nigeria over a period of 15 years, and adequately capture trends of the disease in the region.

## 1.3 Aim and Objectives

The aim of this research is to investigate the trend of occurrence of malaria and typhoid fever in Nigeria. The aim of this research will be achieved through the following specific objectives:

1. Comparison of occurrence of malaria and typhoid fever in Nigeria.
2. Determining the degree of relationship between malaria and typhoid fever
3. Estimation of trend of malaria and typhoid fever in Nigeria.
4. Fit appropriate model to capture the pattern or behavior of malaria cases and typhoid fever in Nigeria.
5. Projecting future value incidence of the diseases.

## 1.4 Relevance of the Research

Most researches conducted on both diseases were done by medical practitioners, who majorly reported the rate of occurrence and major causes of malaria and typhoid fever in the region. Little or no research from the region focuses on future incidence of both diseases if the present situation exists. Such information is important for policymakers to be able to plan ahead of time.

This study will investigate the pattern of occurrence of malaria and typhoid fever in the region over different periods of the year with the aim of forestalling or reducing the danger posed by malaria and typhoid fever, and provides adequate information about the past, present and future of the two diseases in Nigeria.

By adopting a time series analysis approach, this research project will also show how such approach can be used to predict the future incidence of malaria and typhoid fever diseases in the presence of uncertainty.

## 1.5 Scope of the Research

This research work covers a period of 15 years from 2003 to 2017. Information on the number of malaria cases and typhoid fever for the period under study will be obtained and used for this research.

## 1.6 Bibliographic Review

Several works exist in literature on the prevalence of malaria and typhoid fever in Africa and Nigeria in particular with different statistical techniques adopted. According to the malaria fact sheet reported by the United State Embassy in Nigeria, malaria is a risk for 97% of the Nigeria's population with an estimated 100 million cases out of which 300,000 deaths are expected every year. Malaria is expected to cause more deaths in Nigeria when compared to expected deaths from HIV/AIDS every year.

Houmsou et al (2011) determined malaria illness among patients who attended General Hospital Gboko, Benue State Nigeria between June and October 2010 using chi-square. The result obtained revealed that the incidence rate of malaria was not significantly different among the sexes, age group, educational status and occupation of the patients examined.

Ukaegbu et al (2014) studied the incidence of both feverish conditions in patients with fever symptoms in Jos, Plateau State Nigeria. The blood and stool samples of 300 patients with malaria and typhoid fever were collected. A correlation analysis was conducted, and the result showed a strong relationship between two feverish conditions with malaria having more chances of causing fever compared to typhoid infection.

Osagi et al (2015) studied the malaria incidence and typhoid fever simultaneously using Abakaliki, Nigeria as the case study. The blood samples of 250 febrile patients with clinical symptoms of both feverish conditions were collected. Chi-square test was conducted, and the result showed significant relationship between malaria and typhoid fever co-infection and the patient's age and sex while there was no significant relationship with respect to the patient's occupation.

Fana et al (2015) conducted a study on the incidence and threat factors linked with malaria symptom among women that are pregnant in north western Nigeria using chi-square technique. Questionnaire method was employed to obtain primary data from 250 pregnant women in the region. Malaria prevalence in women was found to be significantly associated to their educational status as 63.0% of women with no education tested positive, 45.3% of the women with primary education tested positive, 32.7% of the women with secondary education tested positive while 27.3% of the women with tertiary education tested positive.

Babajide and Perry (2015) investigated the changes in the trend of malaria incidence in Ogun state, Nigeria and assessed the ability of the state in achieving the 2015 millennium goal set to reduce malaria in the state. The result obtained showed that malaria cases increases on a monthly and yearly basis by 0.7% and 9.0% respectively. The malaria cases 2014 and 2015 were forecasted using ARIMA model and the result showed about 164.9% increase in malaria cases for 2015 when compared to 2005 malaria cases. They concluded that Ogun state cannot meet the targeted goal for malaria by 2015 which requires a 75% reduction in malaria cases when compared to 2005 malaria cases.

Ibor et al (2016) examined occurrence and incidence of malaria prevalence in Cross River State, Nigeria from 1983 to 2012 using data collected from the General Hospital Calabar. Using descriptive statistics, a substantial increase in the number of malaria cases was observed from 1986 with the number of malaria cases dropping in 2003. The result revealed an average increase of 75.5% in malaria prevalence from 1983 to 2012. Based on the trend analysis, the highest malaria cases were recorded in December, January, July and February while the lowest was recorded in August and

September with more malaria cases recorded in males when compared to the females. More malaria intervention kits were recommended for both males and females in the area.

Obimakinde and Simon-Oke (2017) researched on the incidence of malaria among patients having the symptoms that conducted malaria test between January and December 2015 at the Federal University of Technology, Akure. Using Chi-square method, malaria incidence with respect to the sexes, status and age group was found to be significant.

Onah et al (2017) identified the challenges confronting the eradication of malaria in Nigeria. Some of the challenges identified are: inadequate healthcare infrastructure in the rural areas, poor distribution of drug, increase in drug resistant parasites and insecticide resistant mosquitoes, poverty and illiteracy. They concluded that much work is still needed to reduce malaria incidence in Nigeria to a minimal level and suggest that combination of several malaria control methods should be applied.

Ishaq and Murtala (2017) studied the dimension and physical pattern of typhoid among youths in Kano city, Kano state Nigeria from 2010 to 2014 using the data obtained from Muhammad Abdullahi Wase Specialist Hospital (MAWSH). G-statistics was used for the analysis and an upward movement in the typhoid prevalence as the age increases. Also, a downward trend movement was observed in the typhoid prevalence from 2010 – 2014 with higher prevalence in males and in the northern part of the metropolis.

Ozofor and Onus (2017) carried out a statistical analysis on the reported cases of malaria in urban area of Enugu State, Nigeria using Parklane Specialist Hospital, Enugu as case study between 2009 and 2015. Regression technique was employed to determine the nature of relationship between malaria and time factor. The results indicated a negative linear relationship between malaria prevalence and the various years considered and the rate of decrease in malaria prevalence is more in males compared to females. It was recommended that areas which serve as breeding site for malaria be made clean.

Anokye et al (2018) studied the pattern of malaria incidence in Kumasi Metropolis using a secondary data obtained from the Regional Health Directorate between 2010 and 2016. An increasing quadratic behavior was observed in both the monthly and mid-year malaria cases with the highest and lowest cases occurring in July and January respectively. The future malaria incidence was forecasted for the monthly and mid-year malaria incidence for the period 2018 and 2019 using Autoregressive Integrated Moving Average (ARIMA (1,1,2)) and quadratic model respectively. The result of the forecast showed a decrease in the malaria cases for 2018 and 2019.

Owoeye et al (2018) decomposed the changes in malaria amongst children under five years old in Nigeria over ten years period between 2003 and 2013. A multivariate decomposition method was used to partition the changes in malaria prevalence into two components namely: changes in determinants (determinants are age, sex, residence, maternal education, wealth index, ownership of Insecticide

Treated Net (ITN) and utilization of ITN which contributed 4.7% to the changes in malaria prevalence) and changes in the effect of determinants which contributed 95.3% to the changes in malaria prevalence.

Akawu et al (2018) studied the dimension of malaria incidence in all the Local Government Areas in Borno State, Nigeria using secondary data obtained from Borno State Epidemiological Unit between 2011 and 2013. The prevalence was categorized into four different levels as a result of the number of cases recorded in each of the years considered. Maiduguri Metropolis and Jere had very high incidence in 2011 while in 2012 and 2013, Ngala LGA joined the former two LGAs with very high malaria prevalence.

Adeboye and Ezekiel (2018) used the ARIMA model to carry out a statistical analysis of malaria morbidity in Nigeria using time series technique. The study was based on the monthly data obtained from the State Hospital in Ilaro, from 2003 to 2015. ARIMA (2,2,3) model was identified as the most appropriate from the various ARIMA models fitted. The forecast from the ARIMA (2,2,3) model indicates a steady increase in malaria prevalence.

Sekubia and Mensah (2019) studied the trend of typhoid fever cases in Cape Coast Metropolis from 2011 to 2015. Secondary data obtained from the District Health Information Management System (DHIMS) was used for the study. Descriptive statistics was employed for the analysis of the study. The result achieved showed that the mean and median age of the malaria cases are 27.07 and 28.06 respectively with the age group for both the mean and median being 20 – 34 and a standard deviation of 4.15. The result indicated that the standard deviations are widely spread for all age groups.

# CHAPTER TWO

# DATA AND METHODS

## 2.1 Data Description

The data for this study comprises of two time series data. The first series presented in table A1 is the monthly cases of malaria from January 2003 to December 2017 consisting of 180 observations. The second series presented in table A2 is the monthly cases of typhoid fever from January 2003 to December 2017 consisting of 180 observations. These two series consist of reported cases of malaria and typhoid fever (i.e. patients who went for test and tested positive). The gender distribution of the patients for both diseases was also obtained. The gender distribution for the malaria cases is presented in table A3 and table A4 while the gender distribution for the typhoid fever is presented in table A5 and table A6. There are several unreported cases of malaria and typhoid fever in Nigeria and this category is excluded from the data for this study. These two series were obtained from Parklane Specialist Hospital in Enugu State due to availability and popularity of the hospital in Enugu sub-urban area. Parklane Specialist Hospital is a teaching hospital that is fully equipped with medical facilities and easily accessible to all parts of the state due to its location. The choice of this hospital is as a result of it being the major government hospital in the state that is accessible to all the populace of the state.

The first step in any time series analysis is to obtain the time plot of the series to visualize the pattern of the series. The time plots for the malaria cases and typhoid fever are presented in figure 1 and figure 2. A decrease in the number of malaria cases can be observed from 2011 to 2013 with a slight increase between 2014 and 2015. However, a decrease can be noticed between 2016 and 2017. In general, there is a decreasing trend in the number of malaria cases over the period under study. A decrease in the number of typhoid fever can be observed from 2012 to 2017. In general, there is a decreasing trend in the number of typhoid fevers over the period under study.

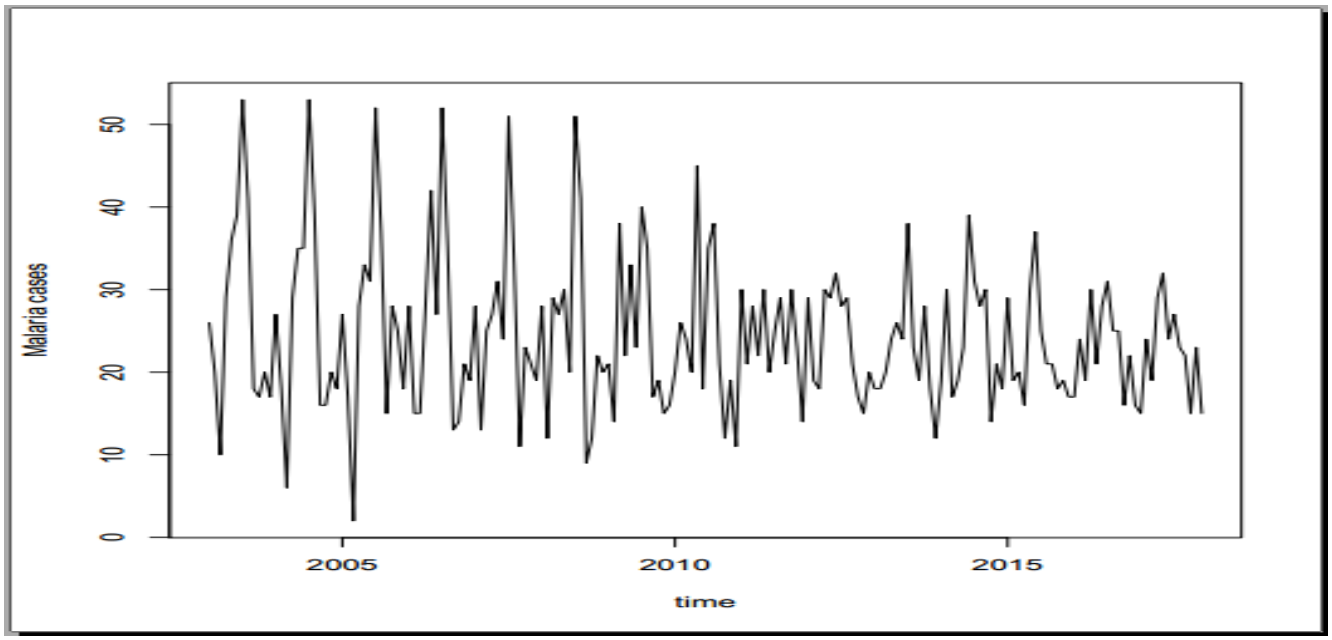


Figure 1: Time plots for the malaria cases

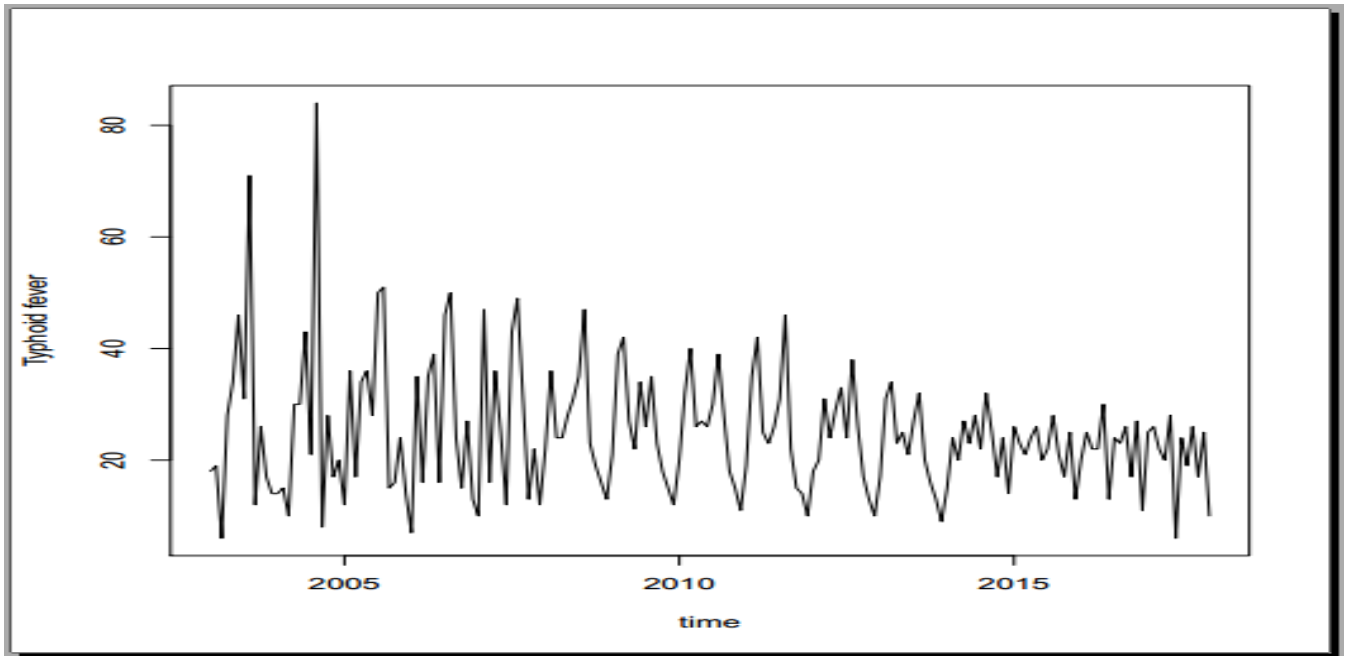


Figure 2: Time plots for the typhoid fever

## 2.2 Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is an approach in statistics used for analyzing data sets with the aim of summarizing their main characteristics or features, preferably using visual methods. Some of the visual methods employed in time series for exploratory data analysis include time plot, decomposed series plot, season plot, etc. In time series analysis, exploratory data analysis starts with the time plot which is the graph of the dependent variable against the time. The time plots for both malaria cases and typhoid fever are presented in figures 1 and 2.

To further understand and visualize some of the hidden characteristics of the series, the series was decomposed into its several components using additive method due to the variability pattern of the series. The reason for decomposition is to separate the components influencing both series to study the pattern of evolvement of these components over time. The decomposed series can be expressed as:

$$X_t = T_t + S_t + C_t + I_t \quad (1)$$

Where,

$X_t$ is the time series

$T_t$ is the trend component

$S_t$ is the seasonal component

$C_t$ is the cyclical component

$I_t$ is the irregular or random component

The plots of the actual series (malaria cases) and its components are presented in figure 3.

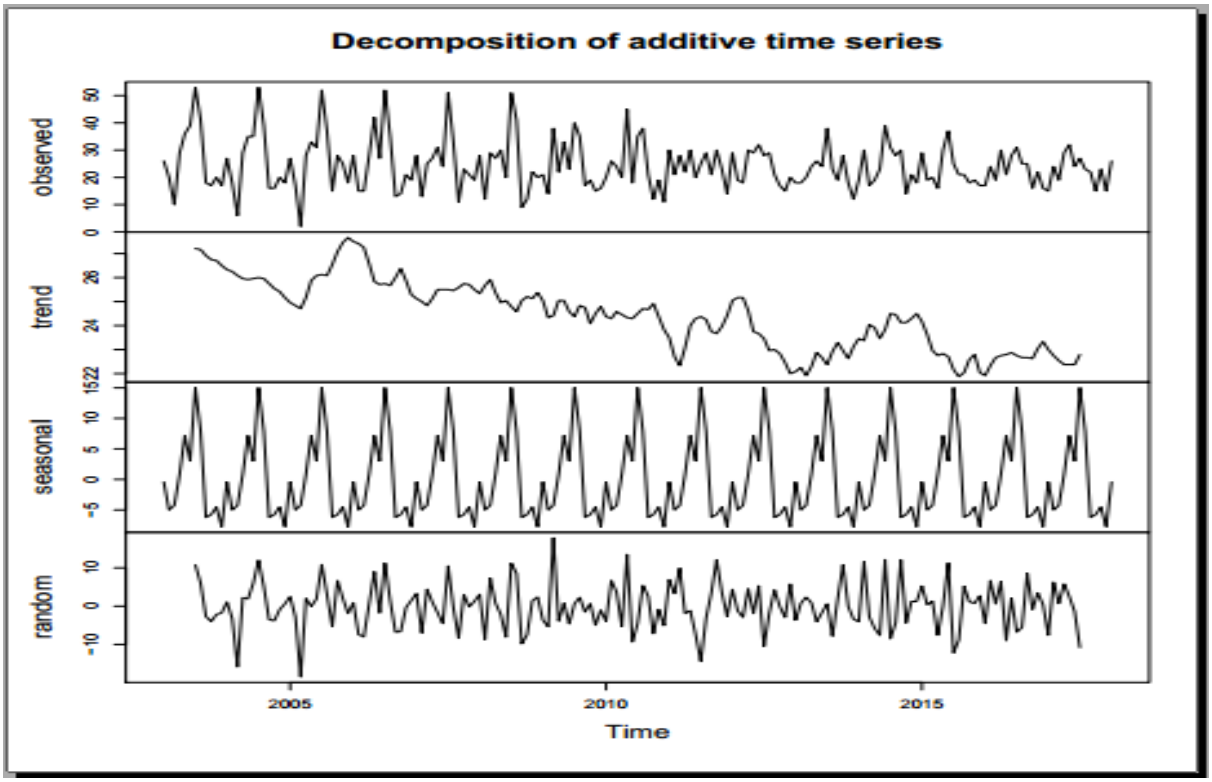


Figure 3: Plots of malaria cases and its components

The plots reveal some interesting features. For the malaria cases, significant spikes were observed from 2003 to 2008 with downward movement observed from 2009 to 2017. This clearly suggests that

the pattern of the malaria cases can be divided into two periods and the pattern differs over the two periods. The practical implication of this is that the variability of the series is not constant over the two periods. To appropriately capture the variability over the two periods, each period will be modeled separately using the autoregressive moving average (ARMA) approach of Box and Jenkins (1970). Also, repeated patterns can be observed in figure 3 indicating the presence of seasonal factor. The seasonal plot for the

malaria cases is presented in figure 4 to further reveal the behavioral pattern of the malaria cases over the months.

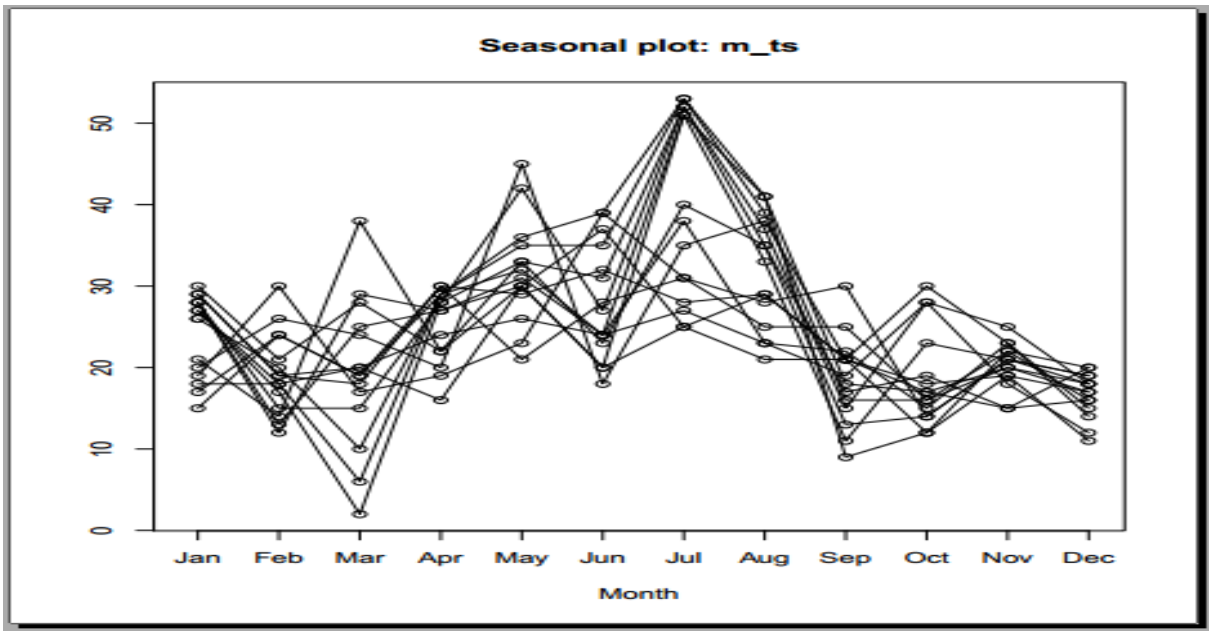


Figure 4: Seasonal plot for malaria cases

The plots of the actual series (typhoid fever) and its components are presented in figure 5.

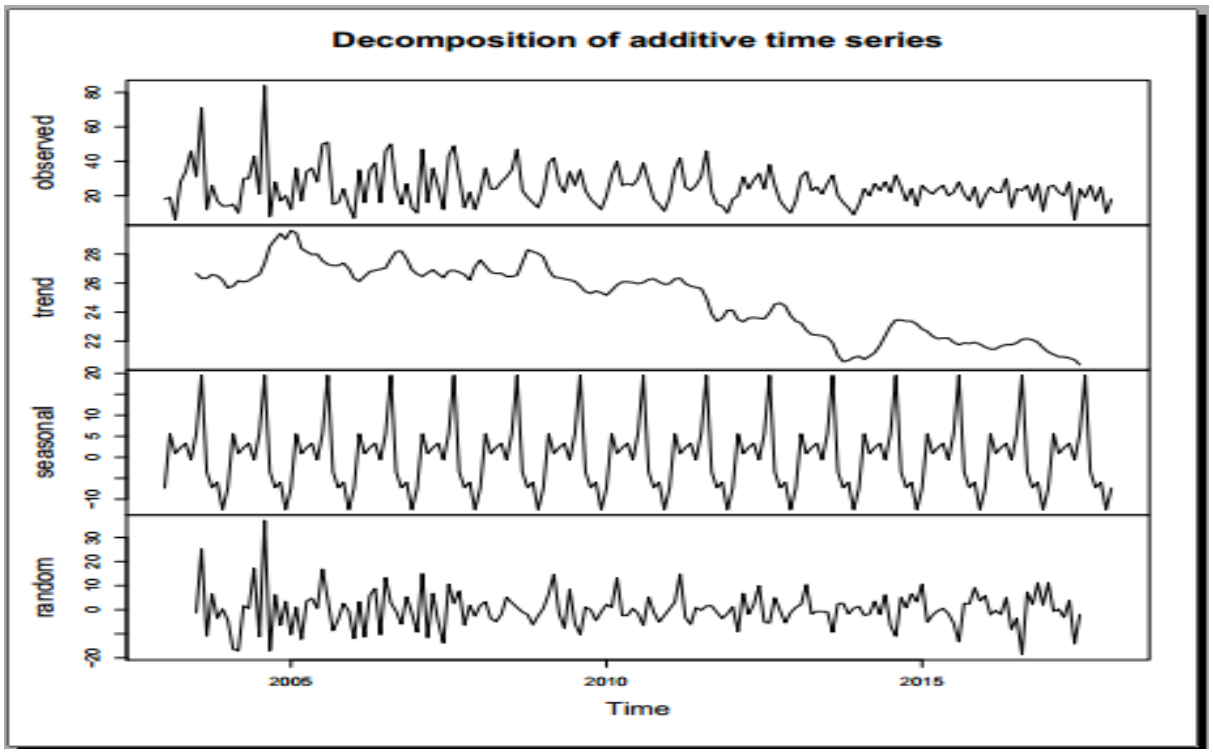


Figure 5: Plots of typhoid fever and its components

For the typhoid fever, significant spikes were observed from 2003 to 2008 with downward movement observed from 2009 to 2017. This clearly suggests that the pattern of the typhoid fever can be divided into two periods and the pattern differs over the two periods. The practical implication of this is that the variability of the series is not constant over the two periods. Also, in other to appropriately capture the variability over the two periods, each period will be modeled separately using the autoregressive integrated moving average (ARIMA) approach of Box and Jenkins (1970). Repeated patterns were observed in figure 5 indicating the presence of seasonal factor. The seasonal plot for the typhoid fever is presented in figure 6 to further reveal the behavioral pattern of the typhoid fever over the months.

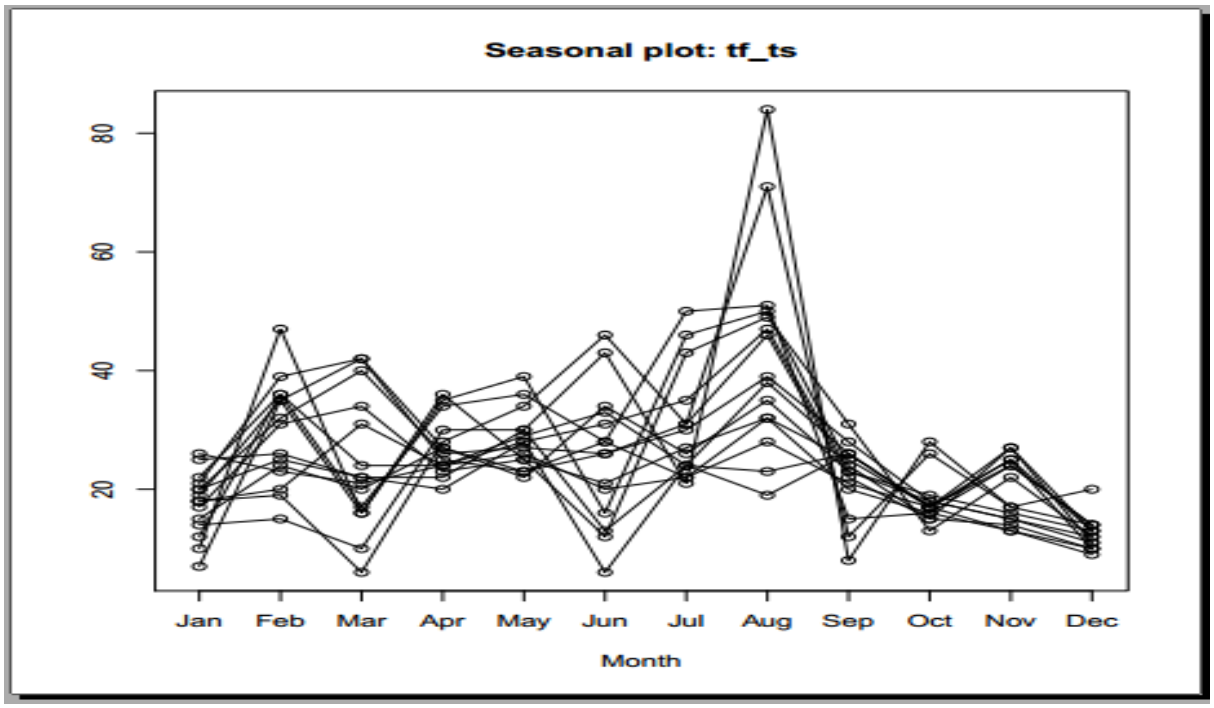


Figure 6: Seasonal plot for typhoid fever

Malaria cases and typhoid fever will be divided into two periods based on the variability across the two periods as discussed above. The malaria cases will now become; malaria cases period one (mp1) from 2003 to 2008 and malaria cases period two (mp2) from 2009 to 2017. Also, the typhoid fever will now become; typhoid fever period one (tp1) from 2003 to 2008 and typhoid fever period two (tp2) from 2009 to 2017. The plots of the two periods for both malaria cases and typhoid fever are presented in figure 7 to figure 10.

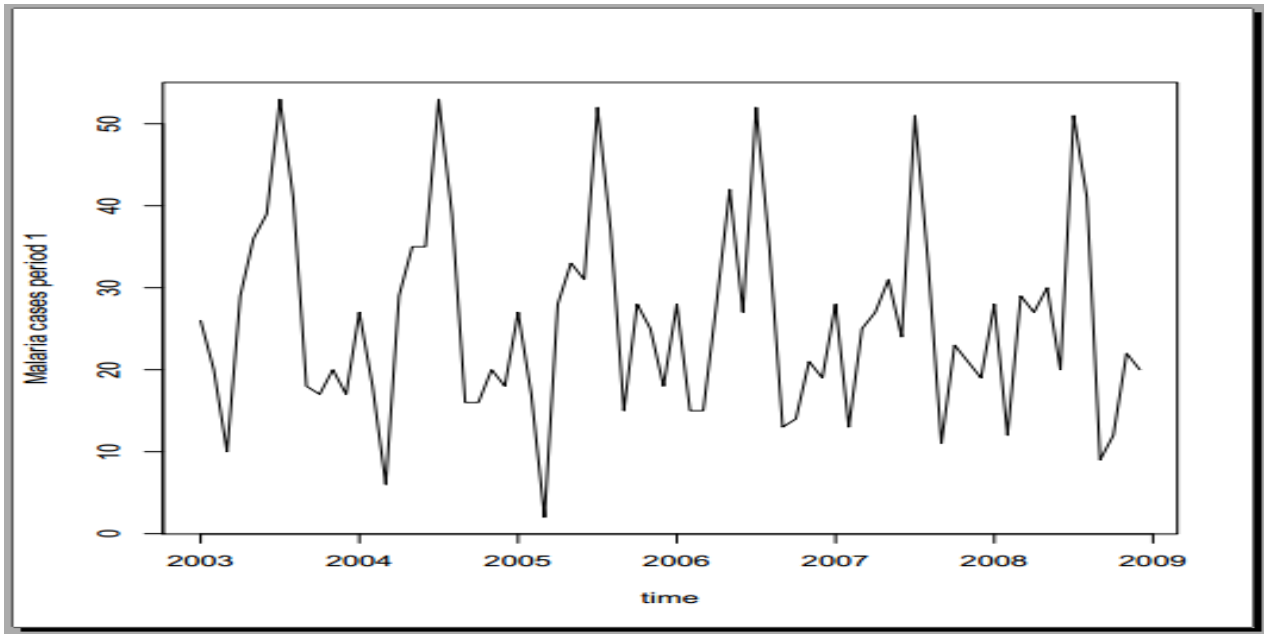


Figure 7: Time plot of malaria cases period one

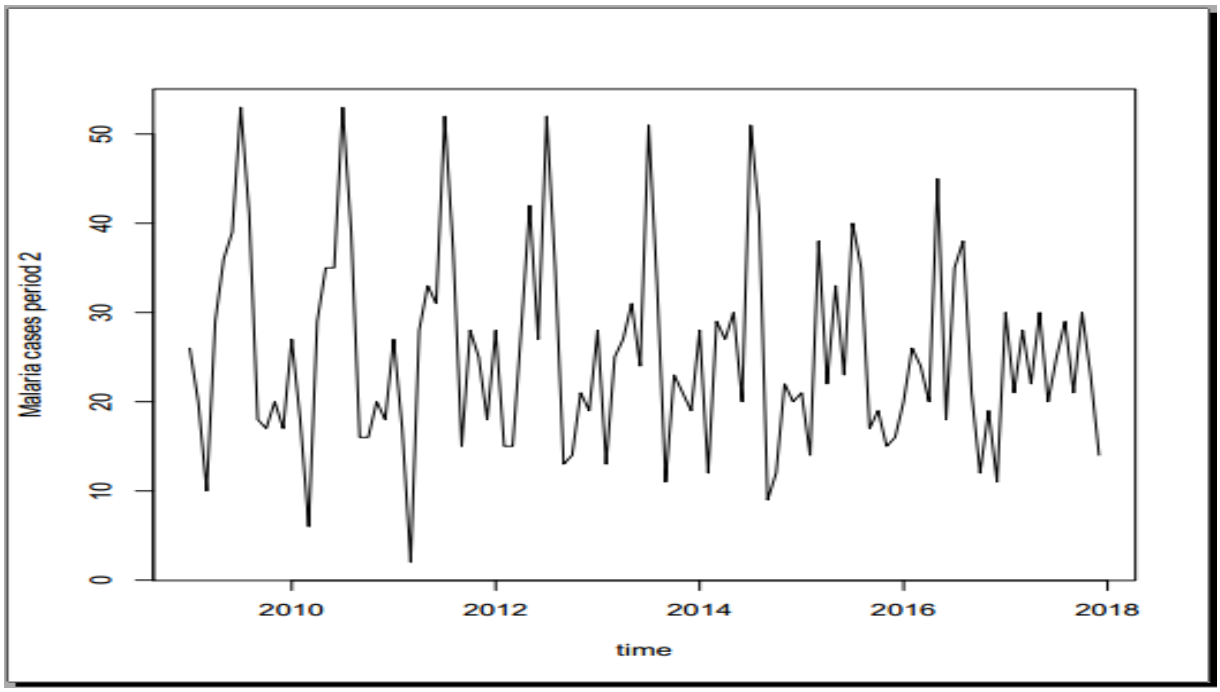


Figure 8: Time plot of malaria cases period two

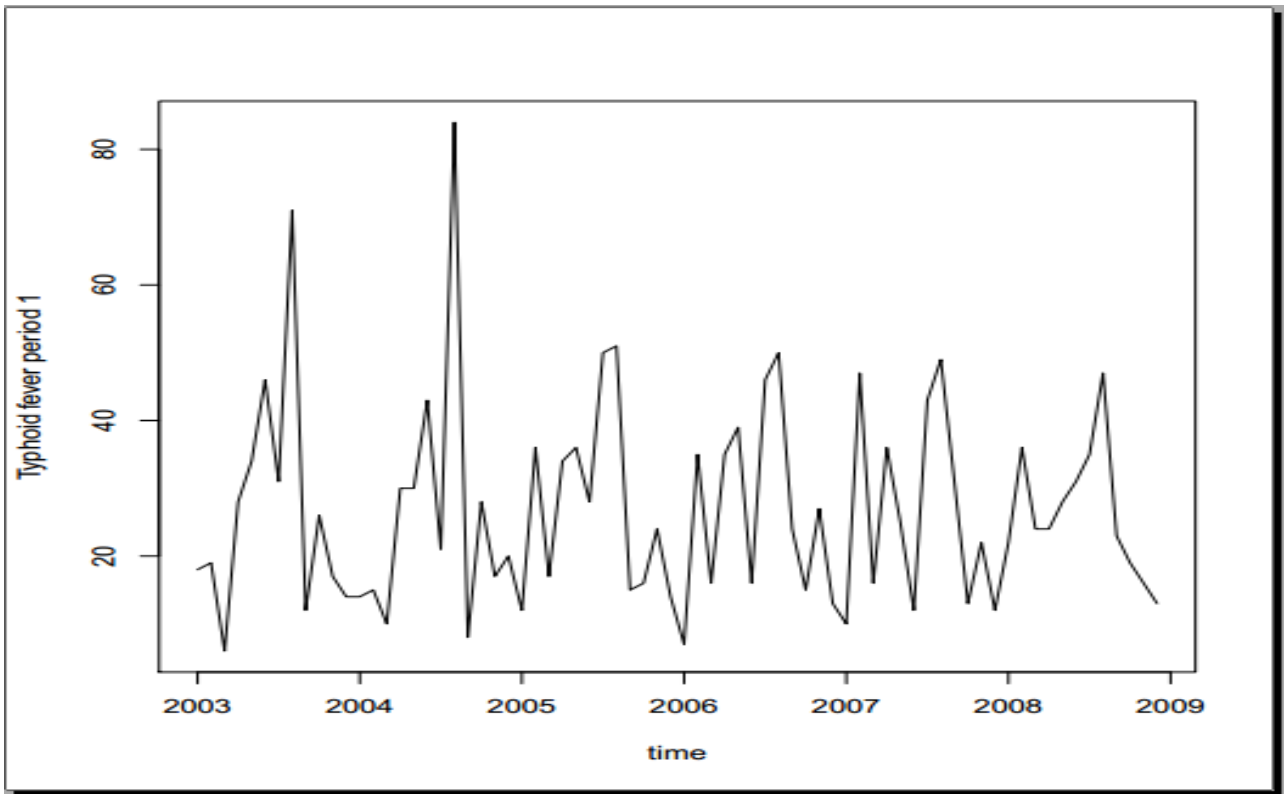


Figure 9: Time plot of typhoid fever period one

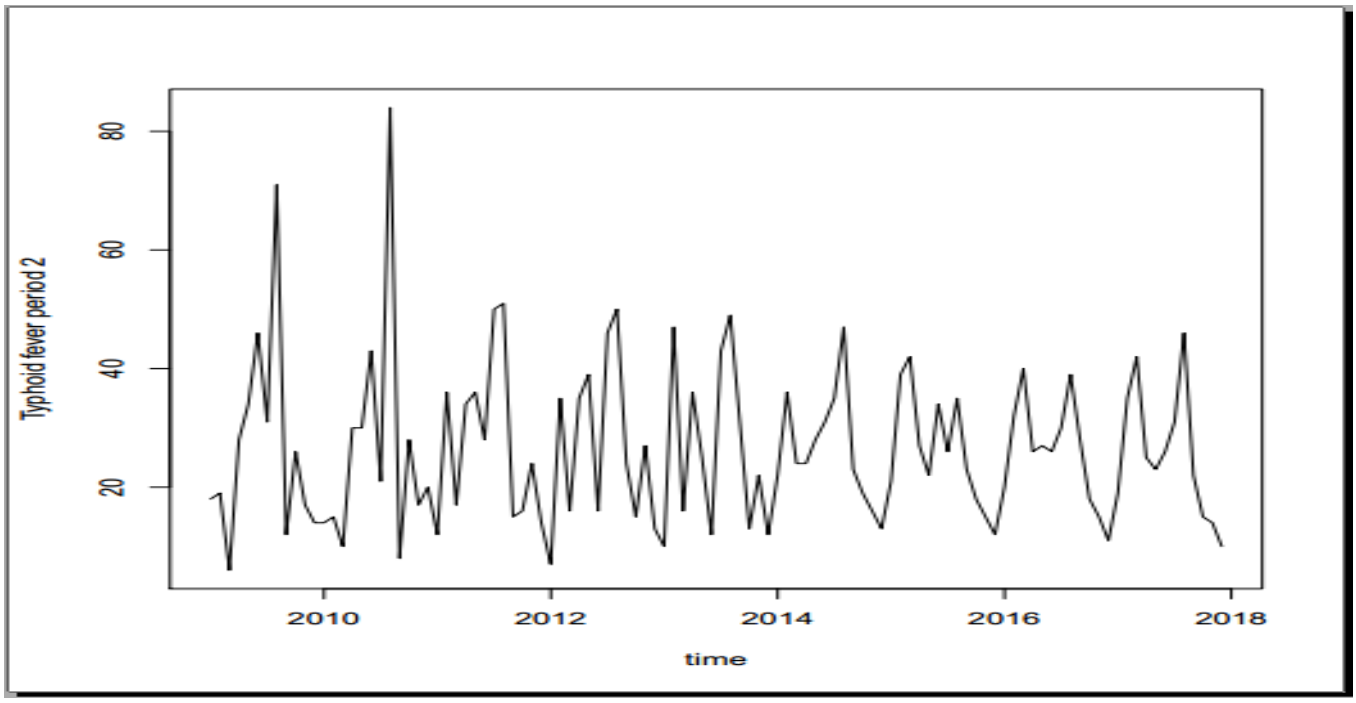


Figure 10: Time plot of typhoid fever period two

## 2.3 Methodology

From the time plots of malaria cases and typhoid fever, both series patterns change around 2009 with evidence of seasonality. The variability across the series differs over the two periods as such constant seasonality cannot be assumed. As discussed above, both series will be partitioned into two namely: period one (2003 to 2008) and period two (2009 to 2017). Arima model will be used capture the seasonal factor present in each period. Trend pattern can be clearly seen in both malaria cases and typhoid fever as presented in figure 3 and figure 5. One of the objectives of this study is to predict future trend of malaria and typhoid fever in the region which might serve as guide for policy makers in curbing the menace of malaria and typhoid fever in the region. The least square method will be used to study the trend pattern in both series and to predict future trend. To fully understand the role of gender in the spread of the diseases, chi-square will be used to determine the association between the diseases and gender. The correlation between the two diseases will be assessed using correlation coefficient.

### 2.3.1 Trend Analysis (Least Square Estimation)

Trend is one of the basic components of a time series. The trend is the general movement (upward or downward) of a series over a long period of time. There several methods of estimating the trend of a given series. However, least square estimation (LSE) and moving average (MA) are commonly used in literature. The LSE method will be used in this work and the trend line equation is given as:

$$Y_t = a + bX_t \qquad (2)$$

Where,

$Y_t$ is the series

a is the intercept

b is the slope

$X_t$is the time variable

$$b = \frac{n\sum_t X_t Y_t - \sum_t X_t \sum_t Y_t}{n\sum_t X_t^2 - (\sum_t X_t)^2}$$

$$a = \bar{Y}_t - \hat{b}\bar{X}_t$$

### 2.3.2 ARIMA MODEL (BOX AND JEKINS)

The Box and Jekins (1970) approach involve three stages namely, identification, estimation and diagnostic checking. The identification process involves identifying or determining the appropriate order of the Auto-Regressive Integrated Moving Average (ARIMA) (p,d,q) required to capture the pattern of the time series using the autocorrelation function (ACF) and partial autocorrelation function (PACF). After the appropriate ARIMA (p,d,q) model, the parameters of the model will be estimated. After identification and estimation, it is required to determine whether the model is adequate, and this is done through diagnostic checking.

ARIMA model is a class of model used for forecasting a stationary time series data. A time series data is said to be stationary if the statistical properties like mean, variance etc. are constant over time. ARIMA model comprises of three parts namely; Auto-Regressive (AR), Integrated (I) and Moving Average (MA) can be classified generally as ARIMA (p,d,q) model, where;

p is the order of the autoregressive term

d is the differencing order required to achieve stationarity

q is the order of the moving average term

The ARIMA (p,d,q) can be expressed mathematically as

$$X_t = \nabla^d x_t \qquad (3)$$

$$x_t = \mu + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \ldots + \varphi_p x_{t-p} - \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_p \varepsilon_{t-p} - \varepsilon_t \qquad (4)$$

Where $X_t$ follows ARIMA (p,d,q) and $x_t$ follows ARMA (p,q) of Box and Jenkins (1970).

If the series is stationary, d will be equal to zero and that leads to the ARMA (p,q) model. However, if the series is differenced d times to achieve stationarity, that leads to ARIMA (p,d,q) model. To determine whether or not the series is stationary, will we test for the presence of unit root. A unit root

helps to identify some features of a series and when unit root is present in a series, it is characterized as stationary otherwise it is non-stationary. The Augmented Dickey-Fuller (ADF) test will be used to test for the presence of unit root.

$$ADF_t = \frac{\emptyset}{SE(\hat{\emptyset})} \quad (5)$$

Where,

$\hat{\emptyset}$ is the least square estimates of the parameters

$SE(\hat{\emptyset})$ is the standard error of $(\hat{\emptyset})$

Hypothesis

$H_o$: $\hat{\emptyset} = 0$ (unit root is present)

$H_1$: $\hat{\emptyset} < 0$(no unit root is present)

When seasonal factor is present in a time series data, the ARIMA model can still be used to describe the behavior of the data taking the seasonal factor into consideration. However, additional components will be added to the model and the model becomes a Seasonal ARIMA (SARIMA) which is denoted as SARIMA (p, d,q)(P,D,Q)s. The additional components (P, D, Q)s are the seasonal components where s is the order of periodicity or seasonality. The SARIMA (p, d,q)(P,D,Q)s is generally expressed mathematically as:

$$\Phi(B^s)\phi(B)\nabla_s^D\nabla^d X_t = \Theta(B^s)\theta(B)\varepsilon_t \quad (6)$$

Where,

$\varepsilon_t$ is a white noise process

B is a backward shift operator

For the model identification, the acf and pacf plots of the stationary series will be observed to determine the order of the model. The table below summarizes the behavior of the acf and pacf plots.

Table 1: Behavior of the acf and pacf of the ARIMA model

| MODEL | ACF | PACF |
|---|---|---|
| AR (p) | Exponential decay/or damped sinusoid | Cuts off after lag p |
| MA (q) | Cuts off after lag q | Exponential decay/or damped sinusoid |
| ARMA (p,q) | Exponential decay/or damped sinusoid | Exponential decay/or damped sinusoid |

The identified model using the acf and pacf plots is called tentative model which will be used as a starting model to search for an adequate model with the least Akaike Information Criteria (AIC).
After the model with the least aic must have been identified, the model will be fitted by estimating the parameters of the model.

The significance of the model coefficients will be examined using z test.

$$Z=\frac{coefficient-0}{S.E\ (coefficient)} \qquad (7)$$

A coefficient will be significantly different from zero if $|Z|$ is greater than $z_{\frac{\alpha}{2}}$ . Taking $\alpha$ =0.05, $z_{\frac{\alpha}{2}}$ = 1.96

The adequacy of the identified model will be assessed by examining the residuals from the fitted model. The Ljung Box test will be used for this purpose. The Ljung Box test will be used to test for absence of serial autocorrelation. The Ljung Box test determines if the residuals are independently identically distributed (i.e. white noise). The Ljung Box test statistic is obtained as:

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j} \qquad (8)$$

Where,

n is the number of observation

$r_j$ is the autocorrelation coefficient in the sample

m is the time lag

Hypothesis

$H_o$= The model is adequate

$H_1$= The model is not adequate

Also, the acf and pacf plots of the residuals will be examined. If the model is found to be adequate, it will be used to forecast the future occurrence of malaria and typhoid fever.

### 2.3.3 Forecasting Methods

The future occurrence of malaria and typhoid fever in the region will be forecasted using the identified arima models. However, the following forecasting methods will be used as benchmarks.

**Mean Method:**

The mean method assumes that all the future values are constant by using the mean of the historical data as the forecast of all the future values. Given $x_1 + x_2 + \cdots + x_T$as the historical data, the forecast value using the mean method is expressed as.

$$\hat{X}_{T+h|T} = \bar{X} = (x_1 + x_2 + \cdots + x_T)/T \quad (9)$$

**Naïve Method**

The naïve method assumes that all the future values are constant by taking the last observation of the historical data as the forecast of all the future values. Given $x_1 + x_2 + \cdots + x_T$as the historical data, the forecast value using the naïve method is expressed as.

$$\hat{X}_{TT+h\,T} = x_T \quad (10)$$

**Seasonal Naïve Method**

The seasonal naïve method uses the last observation in each season as the forecasted future values for each season of the year. Given $x_1 + x_2 + \cdots + x_T$as the historical data, the forecast value using the seasonal naïve method is expressed as.

$$\hat{X}_{T+h|T} = y_{T+h} - m(k+1) \quad (11)$$

**Drift Method**

The drift method uses the average change seen in the historical data over time as the forecast of all the future values. Given $x_1 + x_2 + \cdots + x_T$as the historical data, the forecast value using the drift method is expressed as;

$$\hat{X}_{T+h|T} = x_T + \frac{h}{T-1}\sum_{t=2}^{T}(x_t - x_{t-1}) \quad (12)$$

### 2.3.4 Chi-square test

The chi-square test of association is a statistical technique used in determining whether or not there is significant association between two categorical variables. The null hypothesis is that there is no association between the two categorical variables while the alternative hypothesis is that there is association between the variables. The chi-square test statistic is expressed as:

$$\chi^2 = \sum_{ij}\frac{(O_{ij}-E_{ij})^2}{E_{ij}} \quad (13)$$

Where,

$O_{ij}$is the observed frequency of ith row and jth column

$E_{ij}$is the expected frequency of ith row and jth column

$$E_{ij} = \frac{ith\ row\ total\ X\ jth\ column\ total}{grand\ total}$$

Hypothesis to be tested

$H_o$= There is no association between the gender and diseases

$H_1$= There is association between the gender and diseases

### 2.3.5 Correlation Analysis

For the purpose of this study, the number of malaria cases and typhoid cases will be denoted as X and Y respectively. As mentioned in chapter one, correlation analysis will be used to study the strength of relationship between malaria cases and typhoid fever.

The correlation between malaria and typhoid fever cases will be obtained as.

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{(n\sum x_i^2 - (\sum x_i)^2)(n\sum y_i^2 - (\sum y_i)^2)}} \quad (14)$$

Where,

$r_{xy}$ is the pearson correlation coefficient

n is the number data points

$x_i$ is the number of malaria cases in the ith month

$y_i$ is the number of typhoid fever cases in the ith month

# CHAPTER THREE

# RESULTS AND DISCUSSION

## 3.1 Trend Analysis

As observed from figures 1, 2, 3 and 5, there is trend in both the malaria cases and typhoid fever in the region. As mentioned in chapter one, one of the objectives of this study is to estimate the trend in both the malaria cases and typhoid fever with aim of projecting future trend in the region. Using the least square estimation (LSE), the trend equation for both malaria cases and typhoid fever was obtained as given below.

Malaria cases

Coefficients:

| | Estimate | Std. Error | t value | P-value |
|---|---|---|---|---|
| (Intercept) | 26.95636 | 1.36581 | 19.736 | 0.0000 |
| Slope | -0.02776 | 0.01309 | -2.121 | 0.0353 |

$$Y_t = 26.95636 - 0.02776X_t$$

The coefficients are statistically significant at 95% confidence level since the p-values for both the intercept and slope are less than 0.05

Typhoid fever

Coefficients:

| | Estimate | Std. Error | t value | P-value |
|---|---|---|---|---|
| (Intercept) | 28.68889 | 1.65333 | 17.35 | 0.0000 |
| Slope | -0.04309 | 0.01584 | -2.72 | 0.00717 |

$$Y_t = 28.68889 - 0.04309X_t$$

The coefficients are statistically significant at 95% confidence level since the p-values for both the intercept and slope are less than 0.05

The fitted trend lines for both malaria cases and typhoid fever are presented in figure 11and figure 12, respectively.

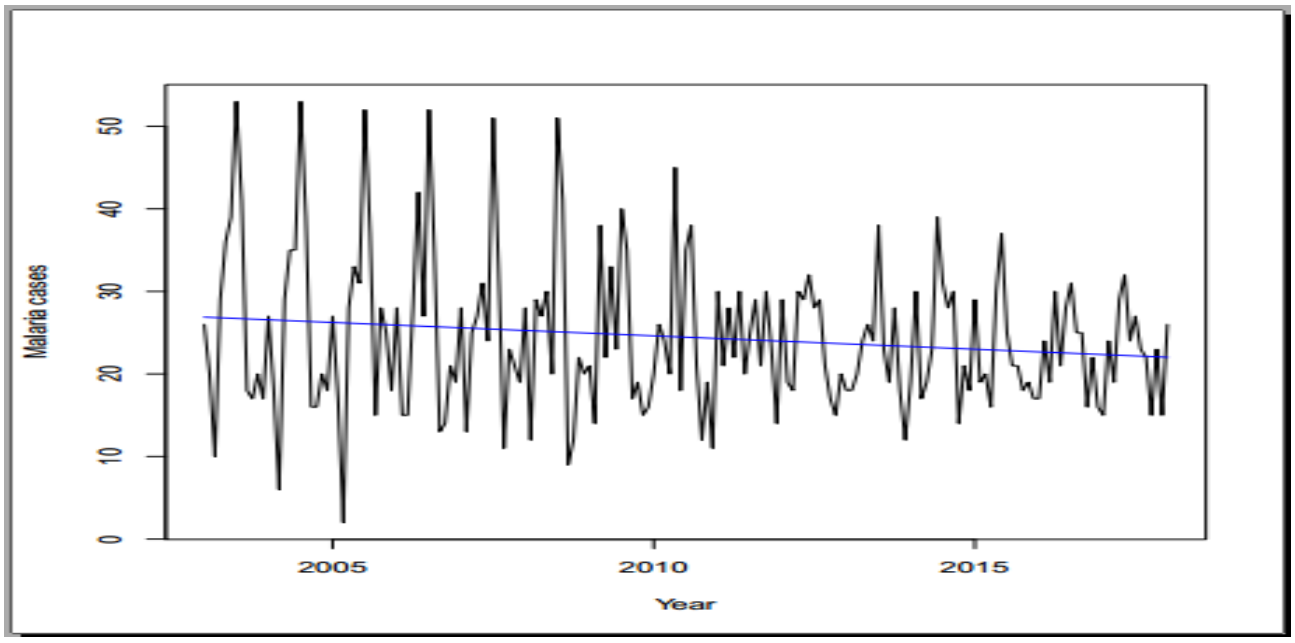


Figure 11: Plot of the fitted line (malaria cases)

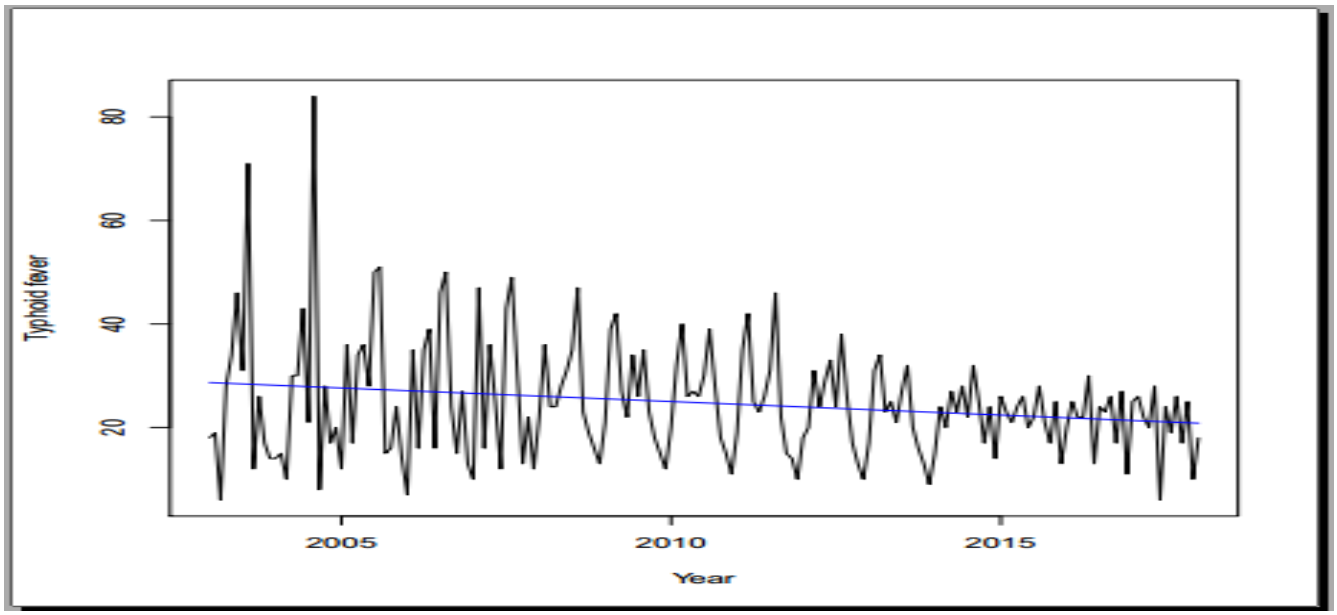


Figure 12: Plot of the fitted line (Typhoid fever)

Having estimated and fitted the trend line to both the malaria cases and typhoid fever, there is needed to use the trend equation to make projections about occurrence of future malaria cases and typhoid fever in the region. Figure 13 and figure 14below indicate a slight decrease in the future occurrence of malaria and typhoid fever in the region.

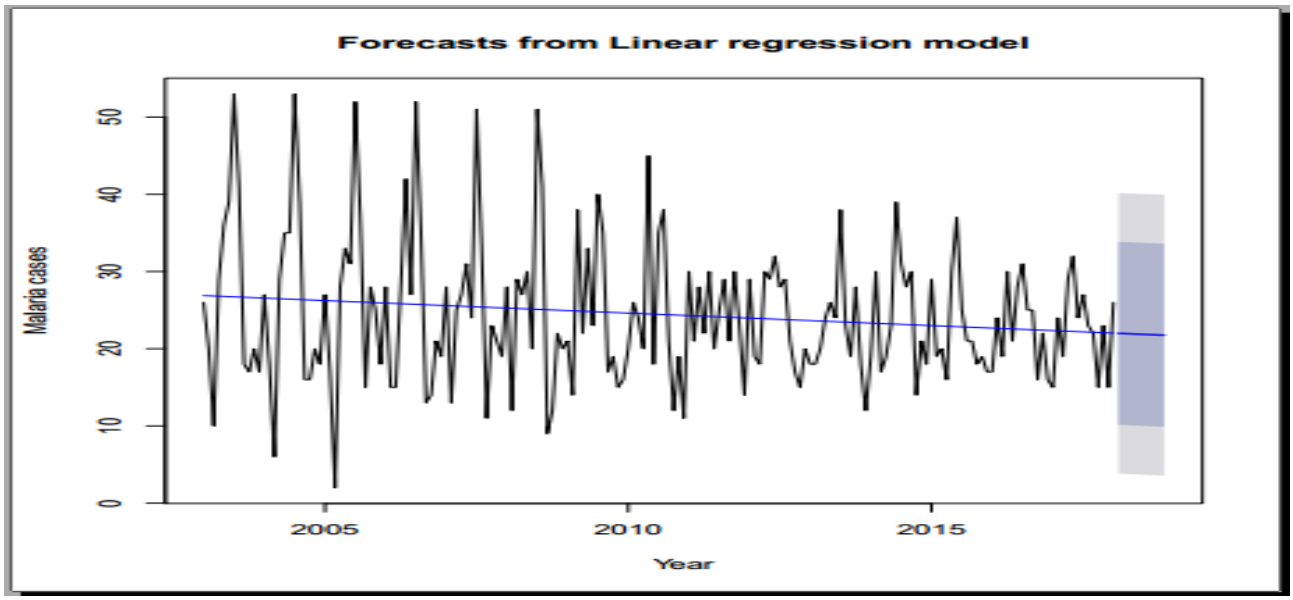


Figure 13: Plot of the forecasted trend line (malaria fever)

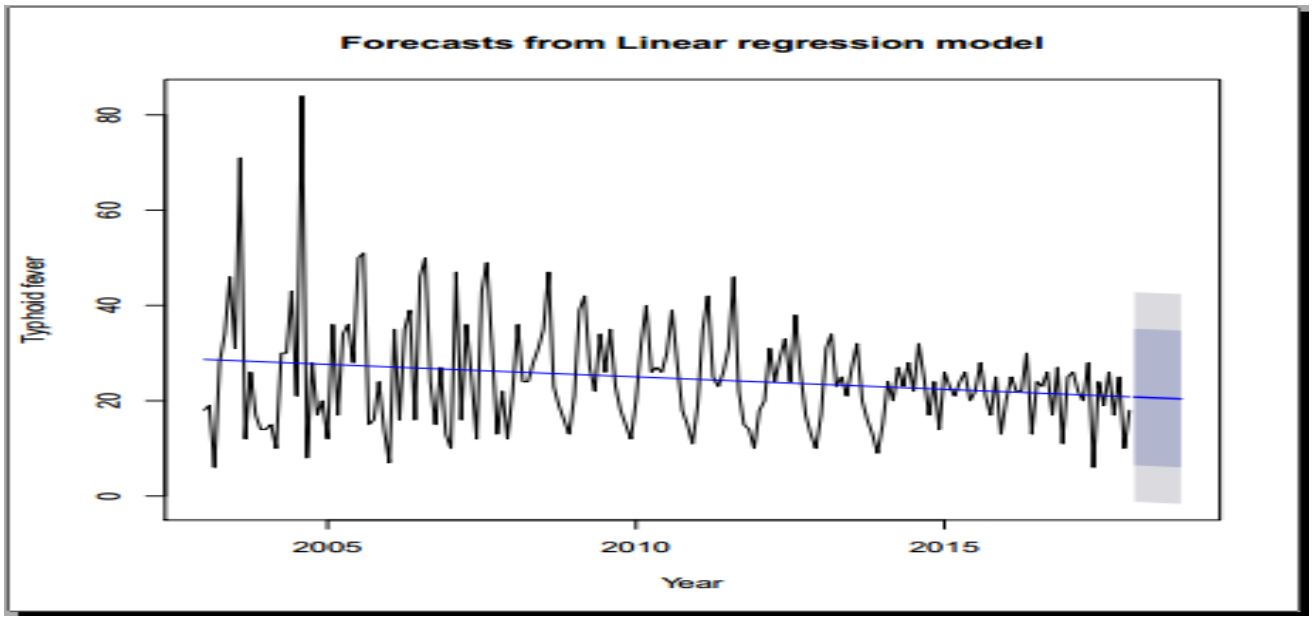


Figure 14: Plot of the forecasted trend line (Typhoid fever)

### 3.2 Arima Model

To better understand the behavior and pattern of occurrence of both the malaria and typhoid fever in the region and make prediction about future occurrence, arima model will be used. One of the important conditions to be considered when using arima model is stationarity. Observing the time plots of malaria under period one and period two presented in figure 7 and figure 8 respectively, no upward, or downward was observed over the period indicating that both series stable. Also, observing the time plots of typhoid fever under period one and period two presented in figure 9 and figure 10

respectively, no upward, or downward movement was observed over the period indicating that both series are stable.

Test of stationarity was carried out on both series under the two periods to determine if they are stationary or not using Augmented Dickey-Fuller (ADF) test. The result for the ADF test conducted for the malaria and typhoid fever series under the two periods is presented below.

**Augmented Dickey-Fuller Test**

**Malaria cases period one**

Dickey-Fuller = -5.4343, Lag order = 4, p-value = 0.01

Null hypothesis: unit root is present (non-stationary)

Alternative hypothesis: unit root is not present (stationary)

The ADF test shows that there is no presence of unit root in the malaria cases period one series.

**Malaria cases period two**

Dickey-Fuller = -7.0389, Lag order = 4, p-value = 0.01

Null hypothesis: unit root is present (non-stationary)

Alternative hypothesis: unit root is not present (stationary)

The ADF test shows that there is no presence of unit root in the malaria cases period two series.

**Typhoid fever period one**

Dickey-Fuller = -6.2764, Lag order = 5, p-value = 0.01

Null hypothesis: unit root is present (non-stationary)

Alternative hypothesis: unit root is not present (stationary)

The ADF test shows that there is no presence of unit root in the typhoid fever period one series.

**Typhoid fever period two**

Dickey-Fuller = -7.3859, Lag order = 4, p-value = 0.01

Null hypothesis: unit root is present (non-stationary)

Alternative hypothesis: unit root is not present (stationary)

The ADF test shows that there is no presence of unit root in the typhoid fever period two series.

Since the p-value = 0.01 is less than 0.05 for the malaria cases period one, the null hypothesis is rejected at $\alpha$ = 0.05 and we conclude that the malaria cases period one is stationary. Also, since the p-value = 0.01 is less than 0.05 for the malaria cases period two, the null hypothesis is rejected at $\alpha$ = 0.05 and we conclude that the malaria cases period two is stationary. Since the p-value = 0.01 is less than 0.05 for the typhoid fever period one, the null hypothesis is rejected at $\alpha$ = 0.05 and we conclude that the typhoid fever period one is stationary.

Also, since the p-value = 0.01 is less than 0.05 for the typhoid fever period two, the null hypothesis is rejected at $\alpha$ = 0.05 and we conclude that the typhoid fever period two is stationary. As mentioned in chapter three, the first step of the arima modeling is model identification by observing the auto-correlation function (ACF) and partial auto-correlation function (PACF) plots. The ACF and PACF plots of the malaria cases under period one are presented in figure 15 and figure 16. The acf plot of the malaria cases period one had significant spike at lags 12, 24 and 36 which indicate the presence of seasonal effect but decays to zero at the seasonal lags indicating a seasonal AR while the pacf cuts off at lag 12 indicating a seasonal AR (1).

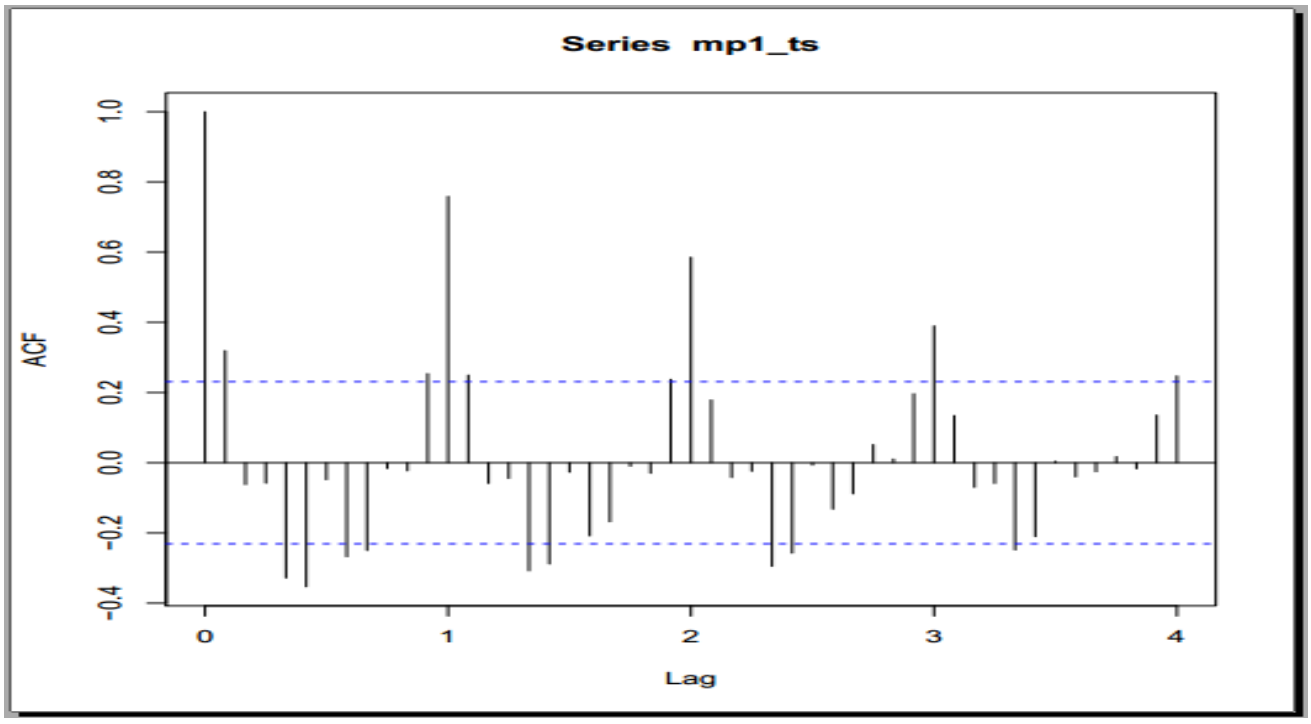


Figure 15: ACF plot of malaria cases period one

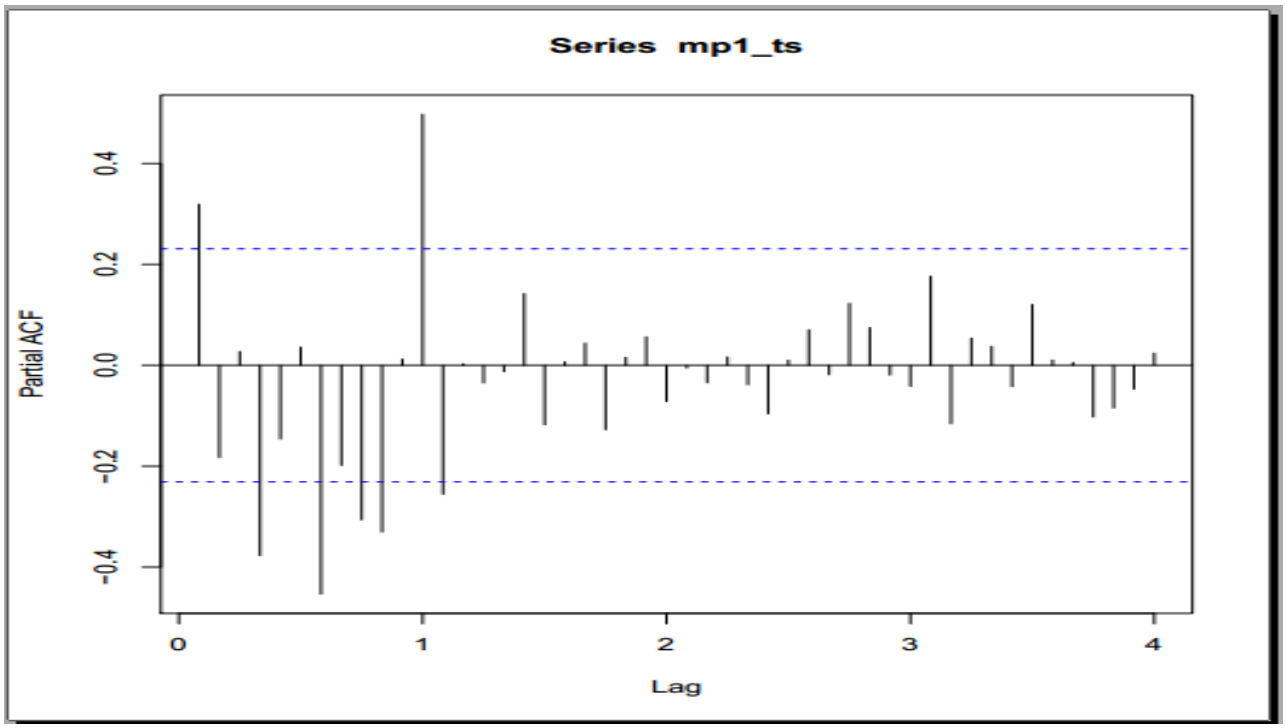


Figure 16: PACF plot of malaria cases period one

The ACF and PACF plots of the malaria cases under period two are presented in figure 17 and figure 18. The acf plot of the malaria cases period two had significant spike at lags 12, 24, 36and 48 which indicate the presence of seasonal effect but decays to zero at the seasonal lags indicating a seasonal AR while the pacf cuts off at lag 12 indicating a seasonal AR (1).

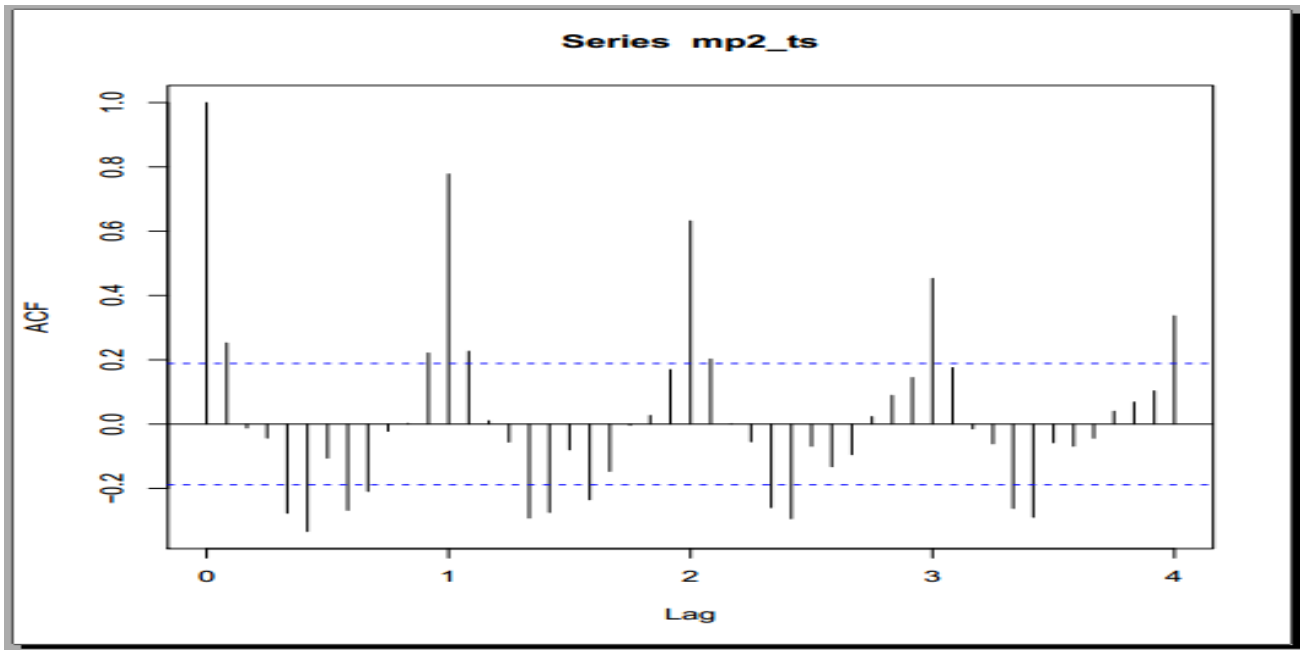


Figure 17: ACF plot of malaria cases period two

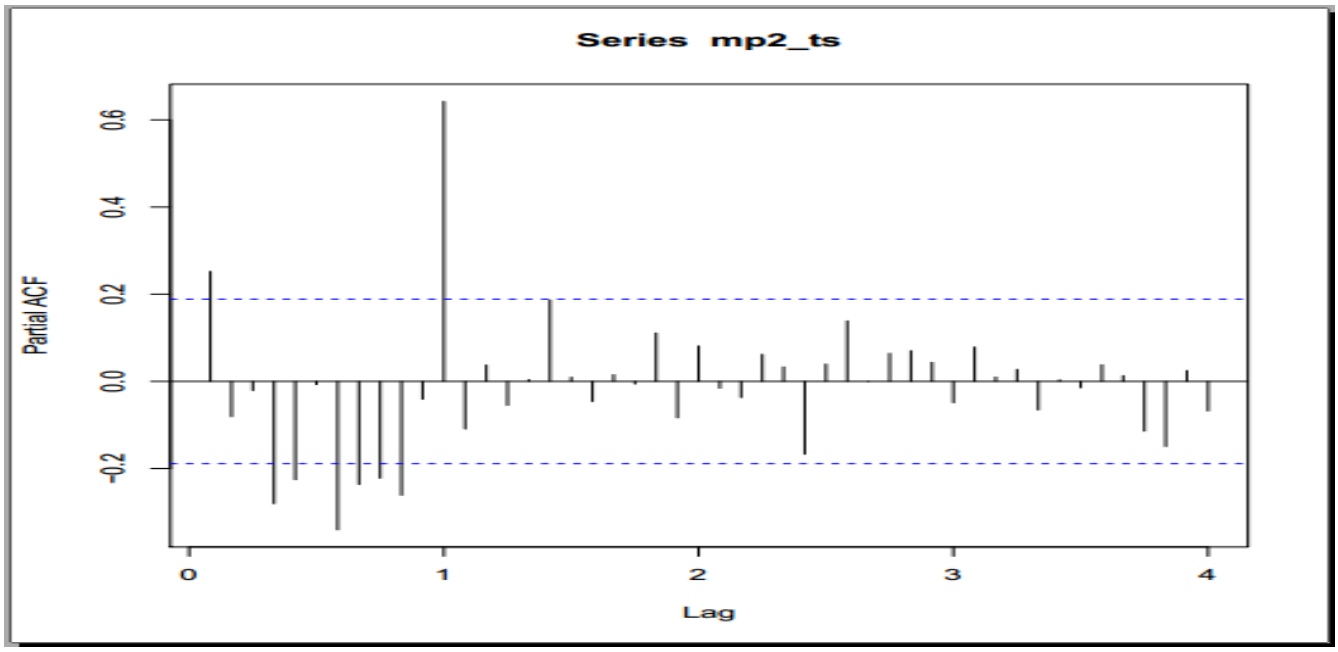


Figure 18: PACF plot of malaria cases period two

The ACF and PACF plots of the typhoid fever under period one are presented in figure 19 and figure 20 below. The acf plot of the typhoid fever period one had significant spike at lags 12 and 24 which indicate the presence of seasonal effect but decays to zero at the seasonal lags indicating a seasonal AR while the pacf cuts off at lag 12 indicating a seasonal AR (1).

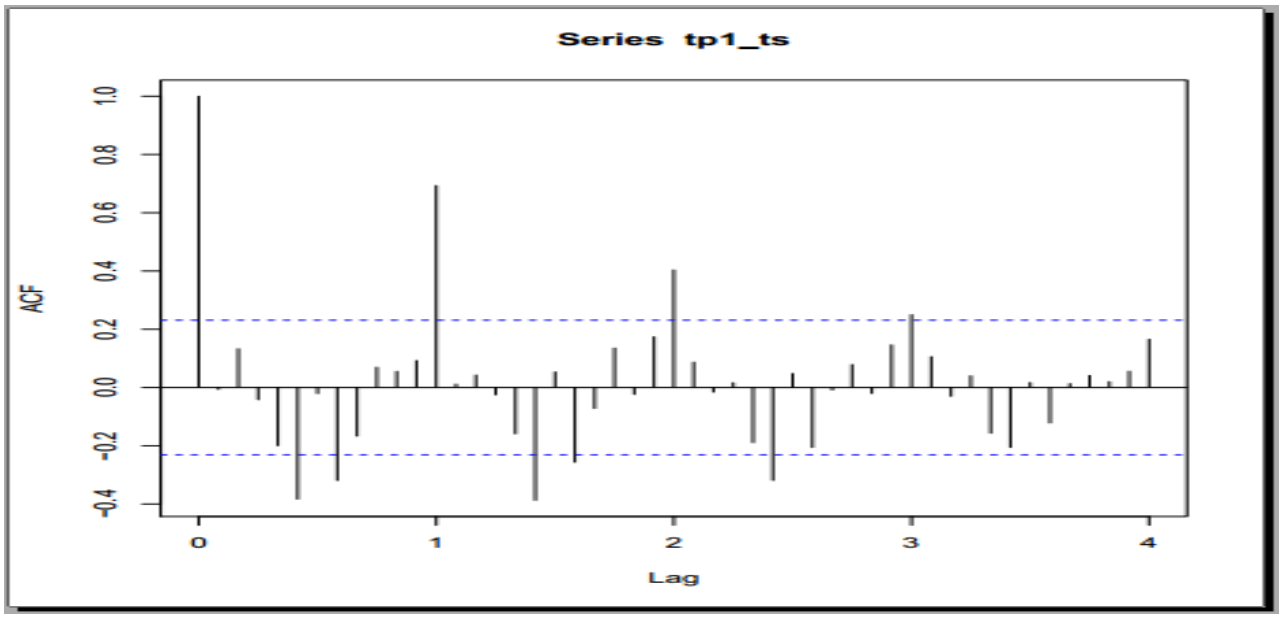


Figure 19: ACF plot of typhoid fever period one

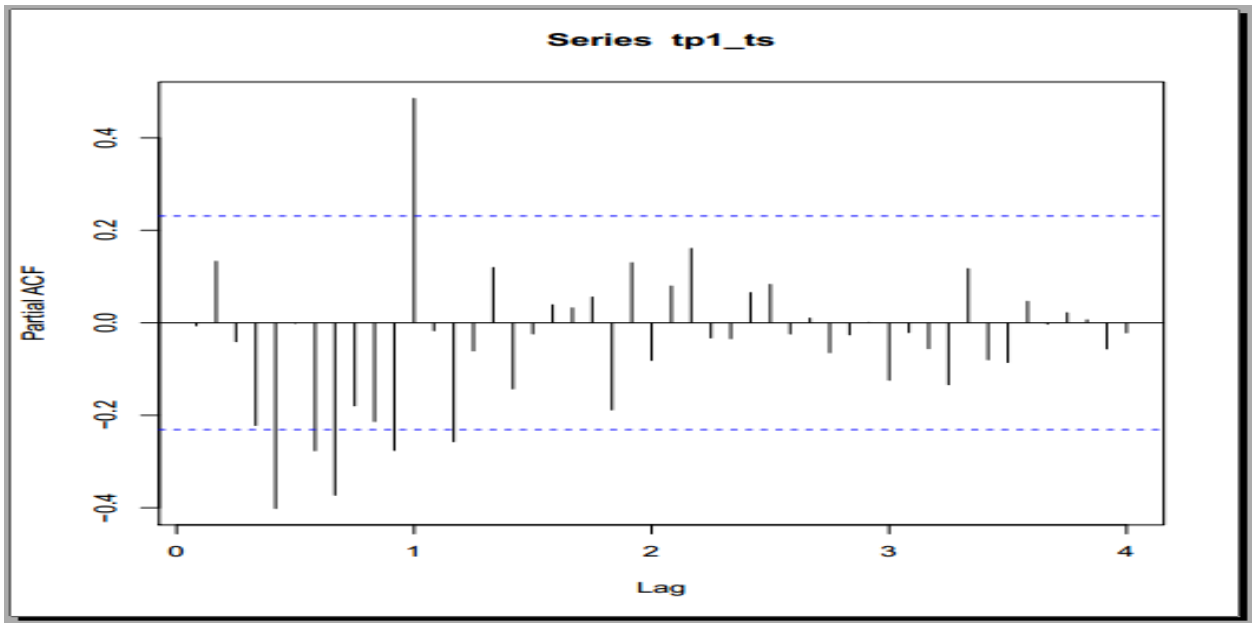


Figure 20: PACF plot of typhoid fever period one

The ACF and PACF plots of the typhoid fever under period two is presented in figure 21 and figure 22. The acf plot of typhoid fever period two had significant spike at lags 12, 24, 36and 48 which indicate the presence of seasonal effect but decays gradually at the seasonal lags indicating a seasonal AR while the pacf cuts off at lag 12 indicating a seasonal AR (1).

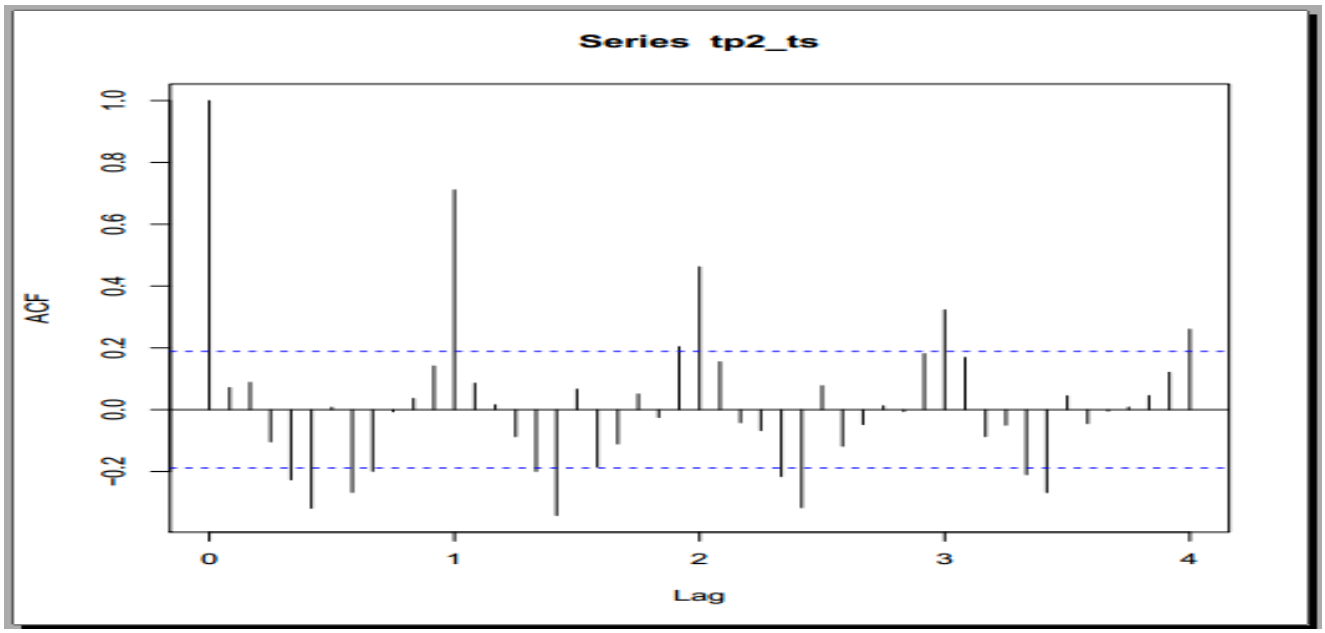


Figure 21: ACF plot of typhoid fever period two

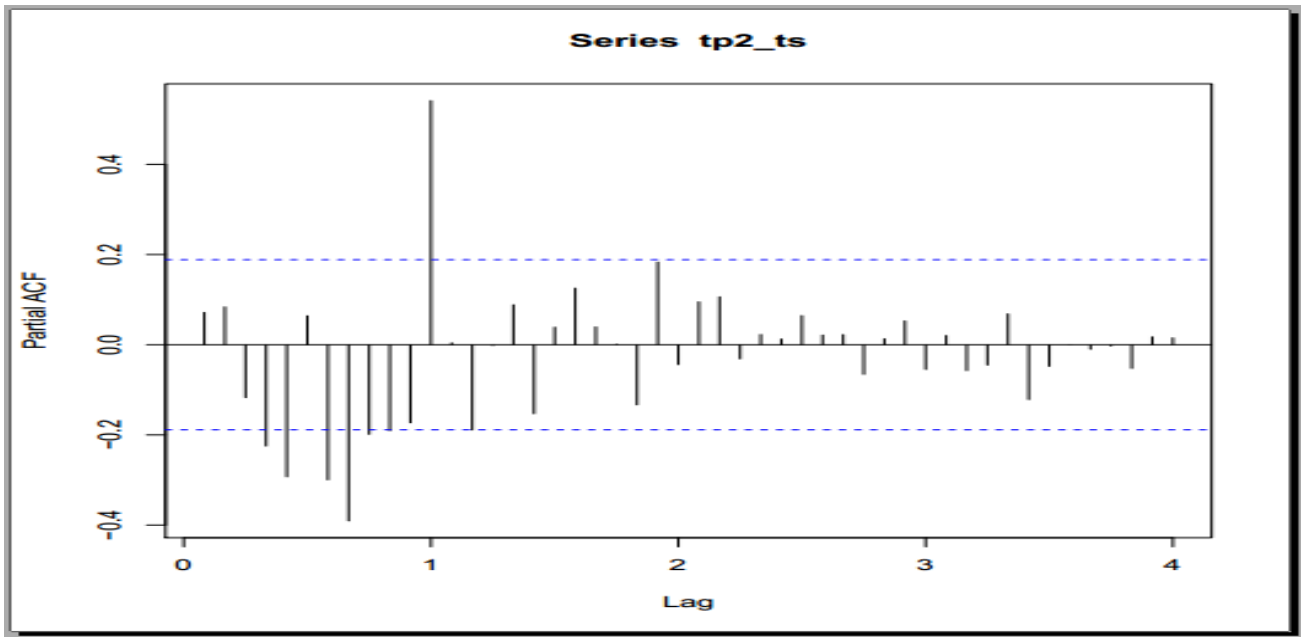

Figure 22: PACF plot of typhoid fever period two

As discussed in the methodology in chapter three that when seasonal factor is present in the data, the seasonal component will be model along with the non-seasonal part which will result to a seasonal arima model known as SARIMA. The auto.arima function in R package was used to search for the best model for both malaria and typhoid fever series under the two periods. The auto.arima function was built to automatically search for the best model among all possible models using all possible combinations of the model parameters. For the malaria cases period one, SARIMA (0,0,0)(1,1,0)[12] with drift was identified as the model with the least information criteria while SARIMA (1,0,1)(1,1,0)[12] was identified as the model with the least information criteria for malaria cases period two. For the typhoid fever period one, SARIMA (2,0,0)(1,1,0)[12] was identified as the model with the least information criteria while SARIMA(1,0,0)(1,1,0)[12] was identified as the model with the least information criteria for typhoid fever period two. Having identified the appropriate model for both series, the parameters of the identified models were estimated as shown below.

**Malaria cases period one**

SARIMA (0,0,0) (1,1,0)[12] with drift

Coefficients:

| | sar1 | drift |
|---|---|---|
| | -0.2534 | -0.0320 |
| s.e. | 0.1377 | 0.0447 |

AIC=286.4 BIC=292.68

The fitted model is expressed as:

$$(1 - \Phi_1 B^{12})\nabla^d X_t = \varepsilon_t + \delta$$

$$(1 + 0.2534B^{12})X_t = \varepsilon_t - 0.0320$$

$$X_t = \varepsilon_t - 0.0320 - 0.2534X_{t-12}$$

**Malaria cases period two**

SARIMA (1,0,1)(1,1,0)[12]

Coefficients:

| | ar1 | ma1 | sar1 |
|---|---|---|---|
| | 0.7318 | -0.8776 | -0.3207 |
| s.e. | 0.1337 | 0.0901 | 0.1055 |

AIC=608.98 BIC=618.09

The fitted model is expressed as:

$$(1 - \Phi_1 B^{12})(1 - \phi_1 B)\nabla^d X_t = (1 - \Theta_1 B^{12})(1 - \theta_1 B)\varepsilon_t$$

$$(1 + 0.3207B^{12})(1 - 0.7318B)X_t = (1 + 0.8776B)\varepsilon_t$$

$$X_t = \varepsilon_t + 0.8776\varepsilon_{t-1} - 0.3207X_{t-12} + 0.7318X_{t-1} + 0.2347X_{t-13}$$

**Typhoid fever period one**

SARIMA(2,0,0)(1,1,0)[12]

Coefficients:

| | ar1 | ar2 | sar1 |
|---|---|---|---|
| | -0.4000 | 0.1212 | -0.2087 |
| s.e. | 0.1272 | 0.0571 | 0.1017 |

AIC=428.94 BIC=438.05

The fitted model is expressed as:

$$(1 - \Phi_1 B^{12})(1 - \phi_1 B - \phi_2 B^2)\nabla^d X_t = 0$$

$$(1 + 0.2067B^{12})(1 + 0.400B - 0.1212B^{2})X_t=0$$

$$X_t = -0.400X_{t-1} + 0.1212X_{t-2} - 0.2067X_{t-12} - 0.0634X_{t-13}0.0253X_{t-14}$$

**Typhoid fever period two**

SARIMA(1,0,0)(1,1,0)[12]

Coefficients:

| ar1 | sar1 |
|---|---|
| -0.3742 | -0.1749 |
| s.e. 0.0946 | 0.0787 |

AIC=661.04 BIC=669.09

The fitted model is expressed as:

$$(1 - \Phi_1 B^{12})(1 - \phi_1 B)\nabla^1 X_t = 0$$

$$(1 + 0.3742B^{12})(1 + 0.1749B)X_t=0$$

$$X_t = -0.1749X_{t-1} - 0.3742X_{t-12} - 0.0654X_{t-13}$$

**Significance of the model coefficients**

**Malaria cases period one**

SARIMA (0,0,0) (1,1,0)[12] with drift

| Coefficients | $\|Z\|$ |
|---|---|
| sar1 | 1.9843 |
| drift | 0.7159 |

The sar1 coefficient is significantly different from zero while the drift coefficient is not significantly different from zero.

**Malaria cases period two**

SARIMA (1,0,1)(1,1,0)[12]

Coefficients $|Z|$

ar1 5.4734

ma1 9.7403

sar1 3.0398

The ar1, ma1and sar1 coefficients are significantly different from zero since all the calculated $|Z|$ are greater than 1.96

**Typhoid fever period one**

SARIMA (2,0,0)(1,1,0)[12]

Coefficients $|Z|$

ar1 3.1447

ar2 2.1226

sar1 2.0521

The ar1, ar2 and sar1 coefficients are significantly different from zero since all the calculated $|Z|$ are greater than 1.96

**Typhoid fever period two**

SARIMA (1,0,0)(1,1,0)[12]

Coefficients $|Z|$

ar1 3.9556

sar1 2.2224

The ar1 and sar1 coefficients are significantly different from zero since all the calculated $|Z|$ are greater than 1.96

It is necessary to consider the adequacy of the model in describing the behavior of the data by examining the residuals from the identified models. This in time series is known as diagnostic checking. The plots of the residuals from the selected models for both malaria cases and typhoid fever are presented in figure 23 to figure 26.

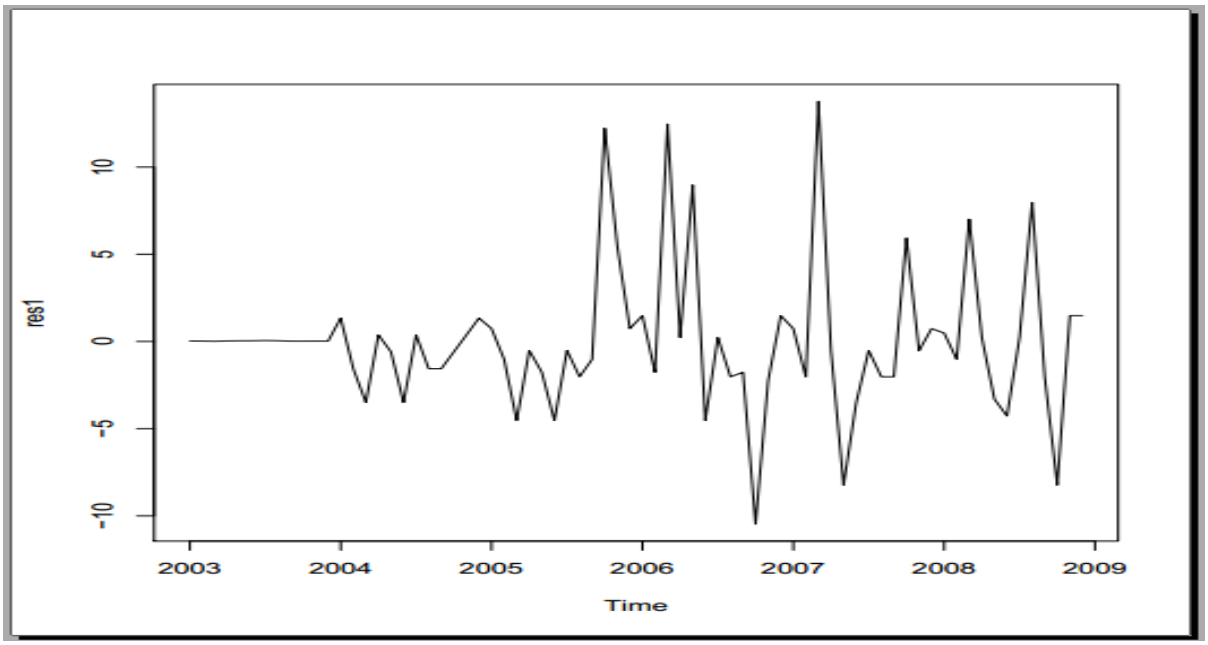


Figure 23: Residual Plot (Malaria cases period one)

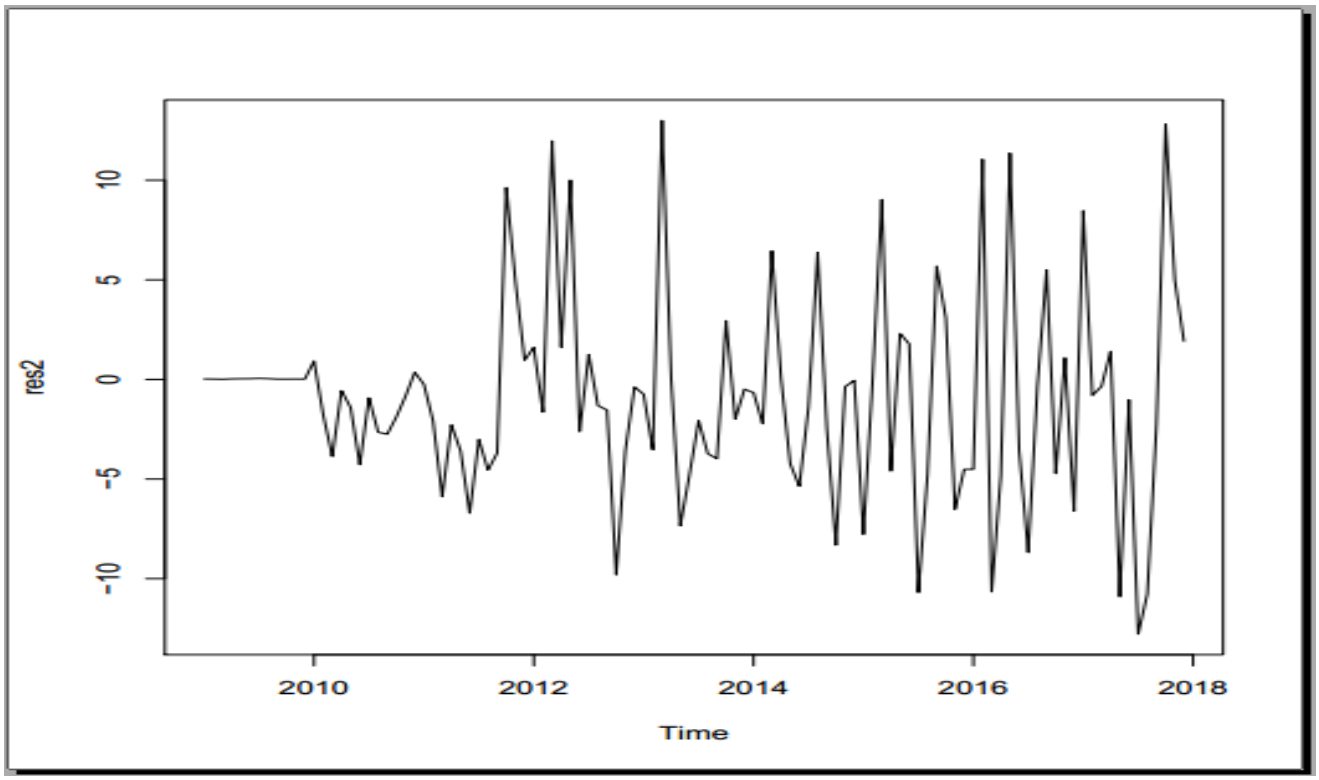


Figure 24: Residual Plot (Malaria cases period two)

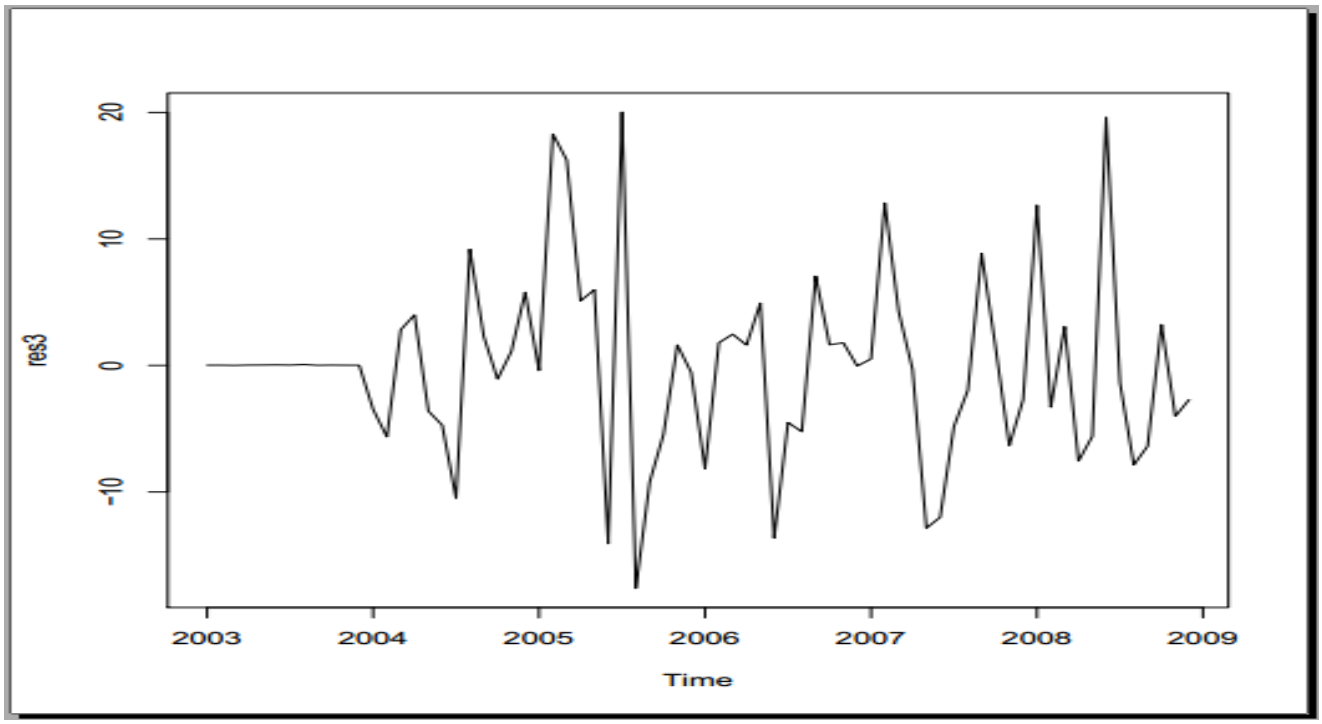


Figure 25: Residual Plot (Typhoid fever period one)

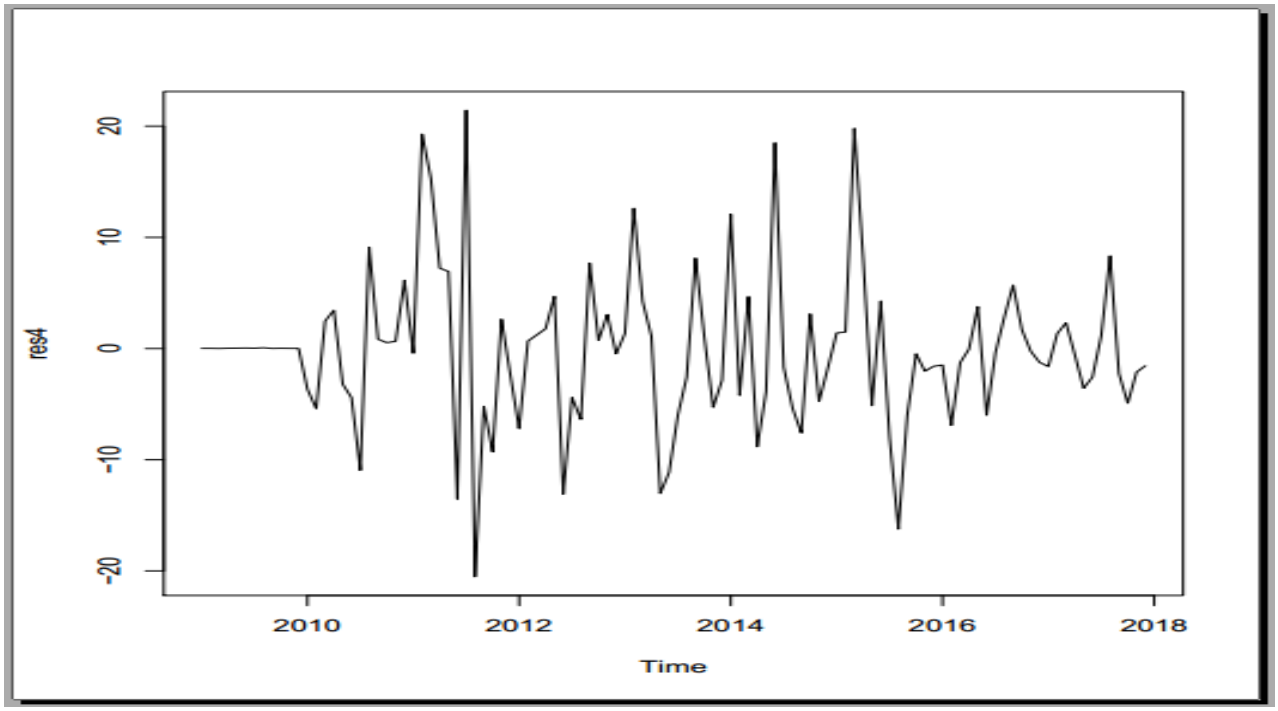


Figure 26: Residual Plot (Typhoid fever period two)

To further understand the behavior of the residual, the acf and pacf of the residuals will be examined. The acf and pacf plots for the residuals are presented in figure 27 to figure 34.

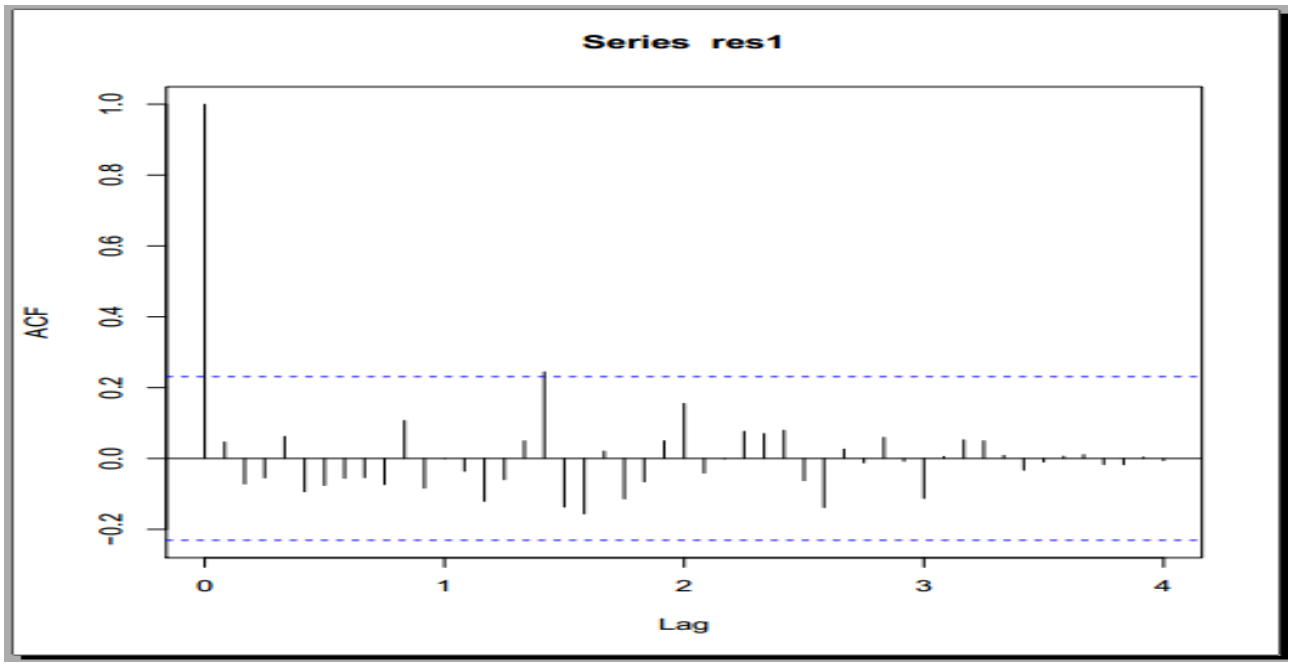


Figure 27: Residual ACF Plot (Malaria cases period one)

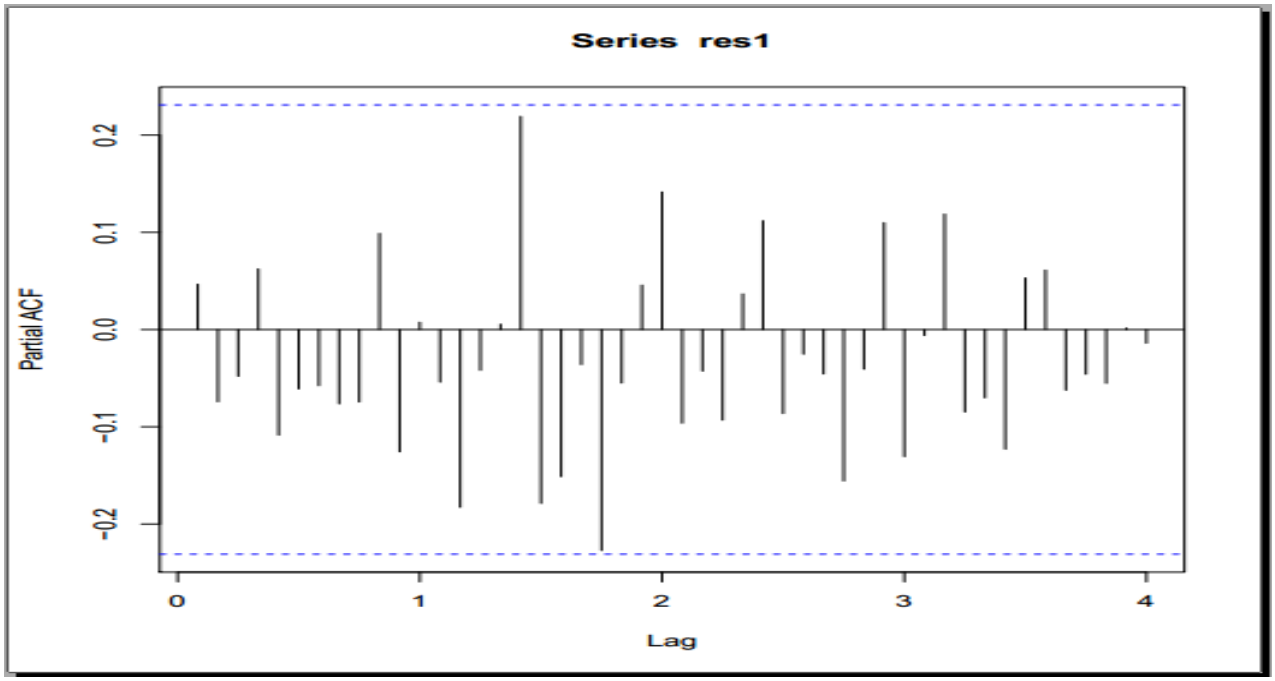


Figure 28: Residual PACF Plot (Malaria cases period one)

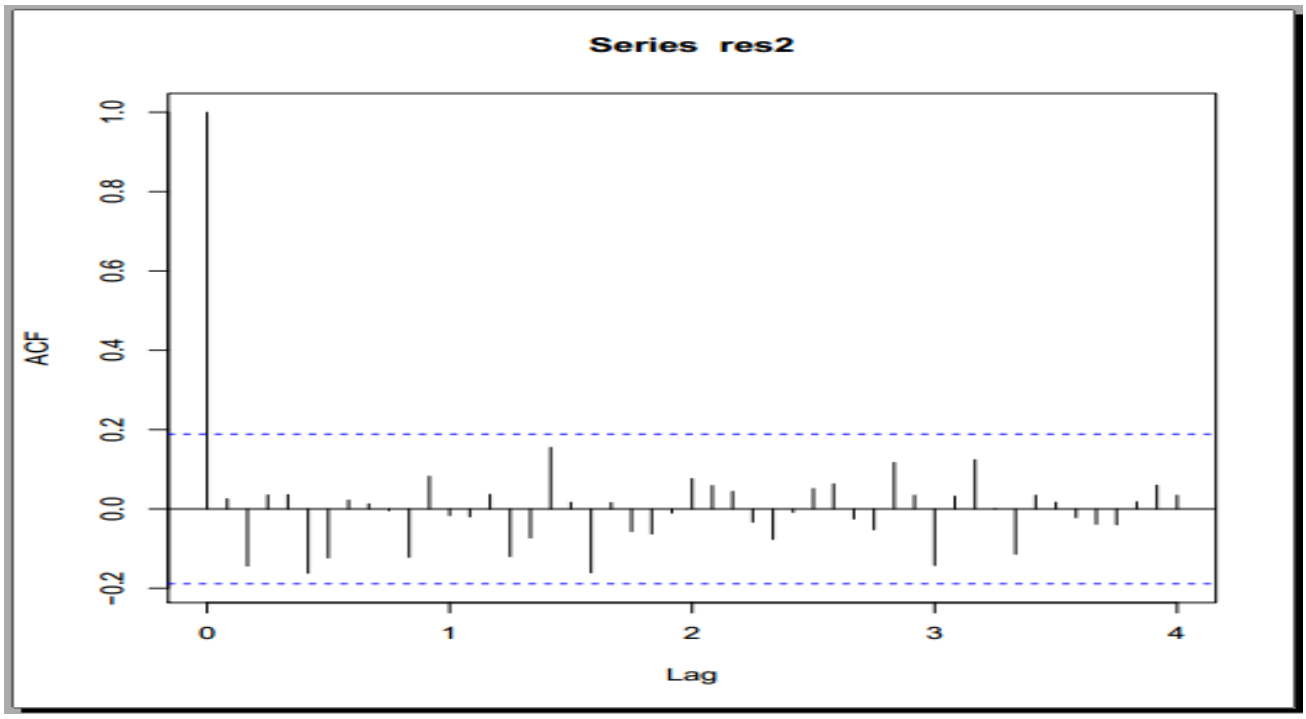


Figure 29: Residual ACF Plot (Malaria cases period two)

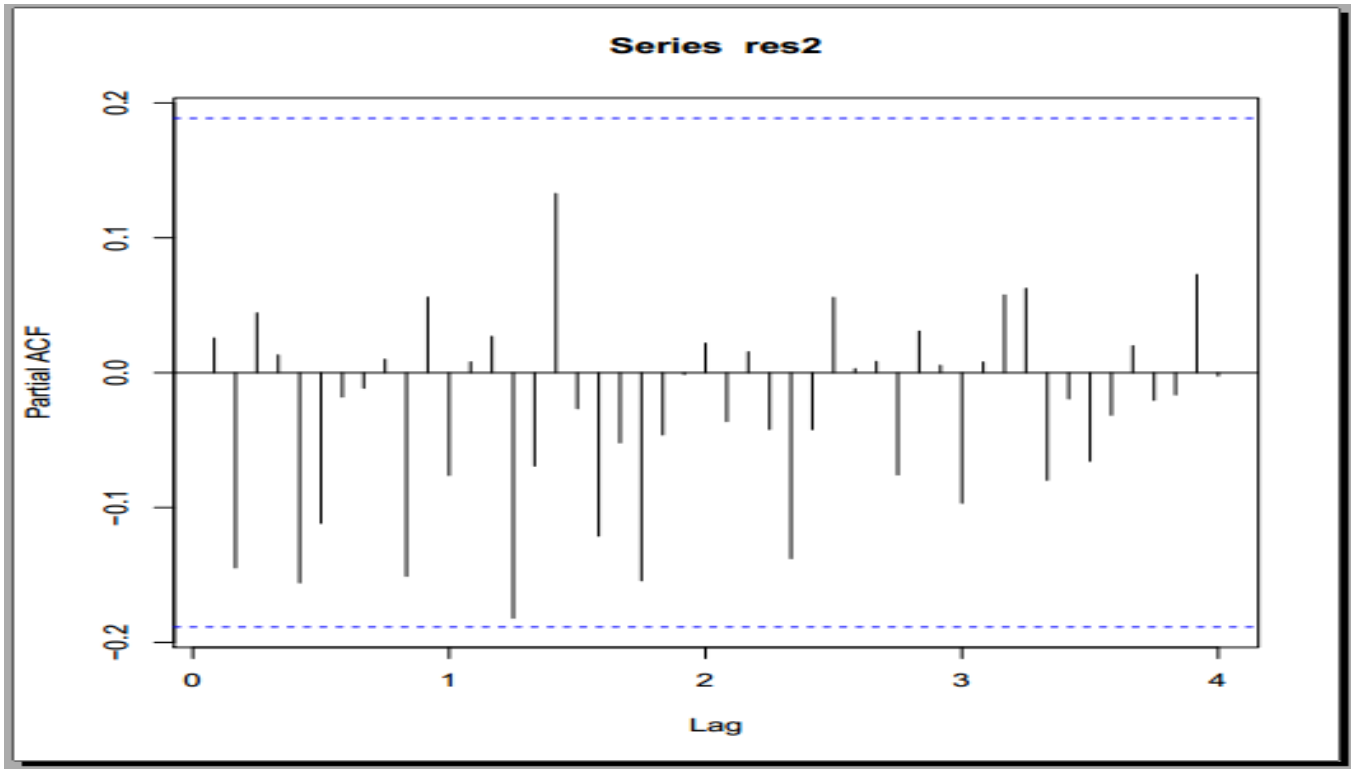


Figure 30: Residual PACF Plot (Malaria cases period two)

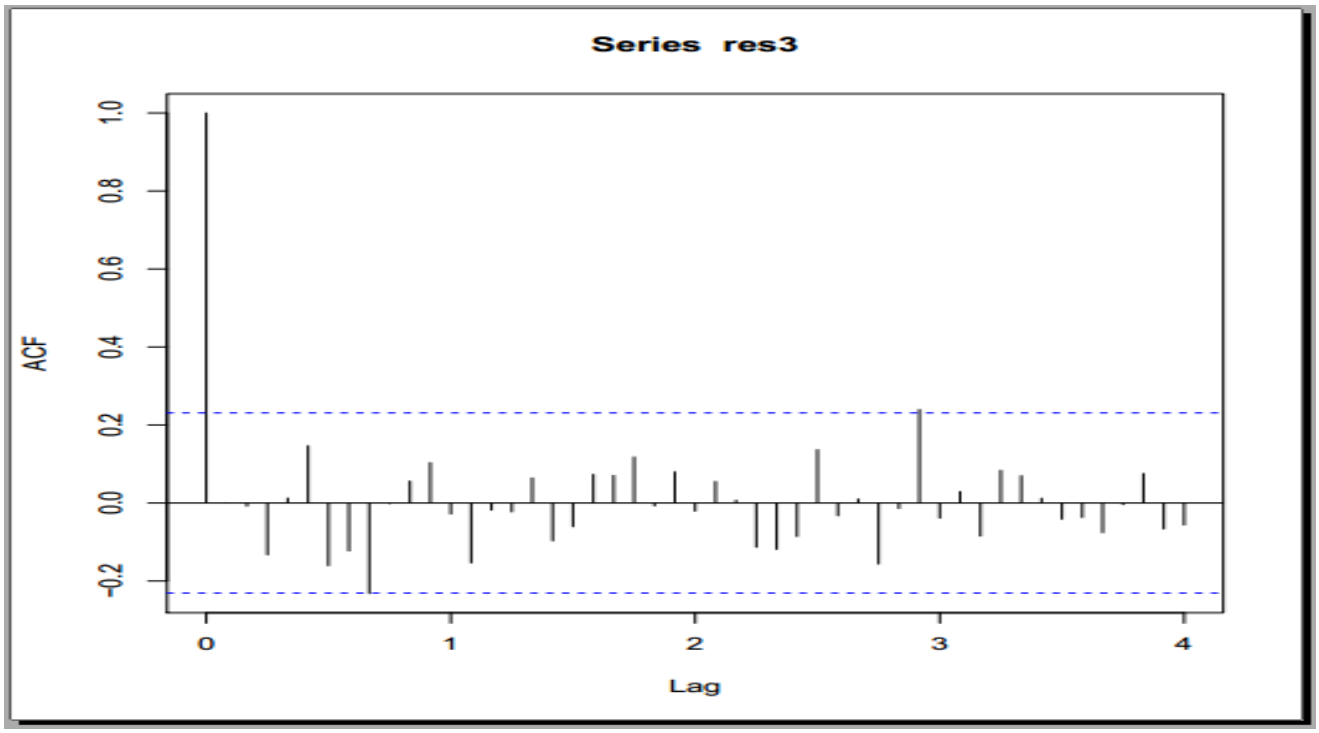


Figure 31: Residual ACF Plot (Typhoid fever period one)

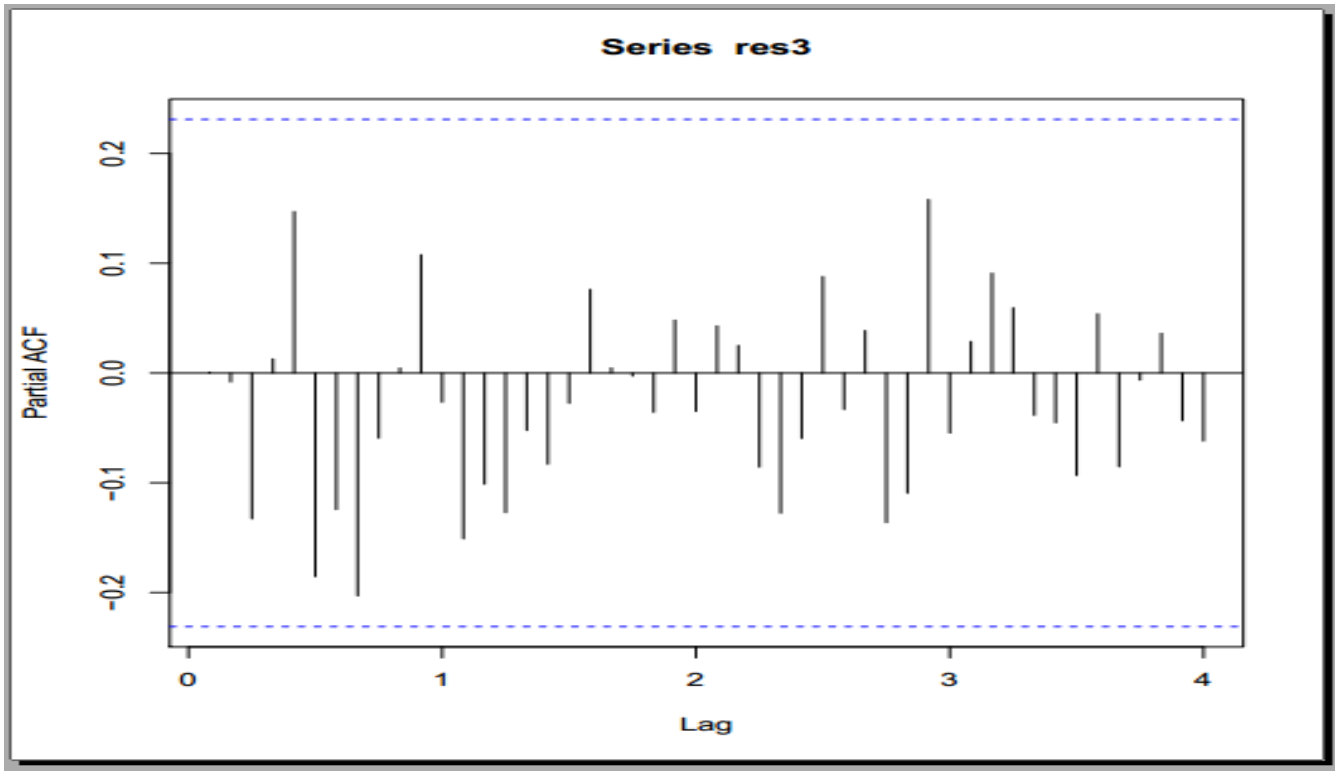


Figure 32: Residual PACF Plot (Typhoid fever period one)

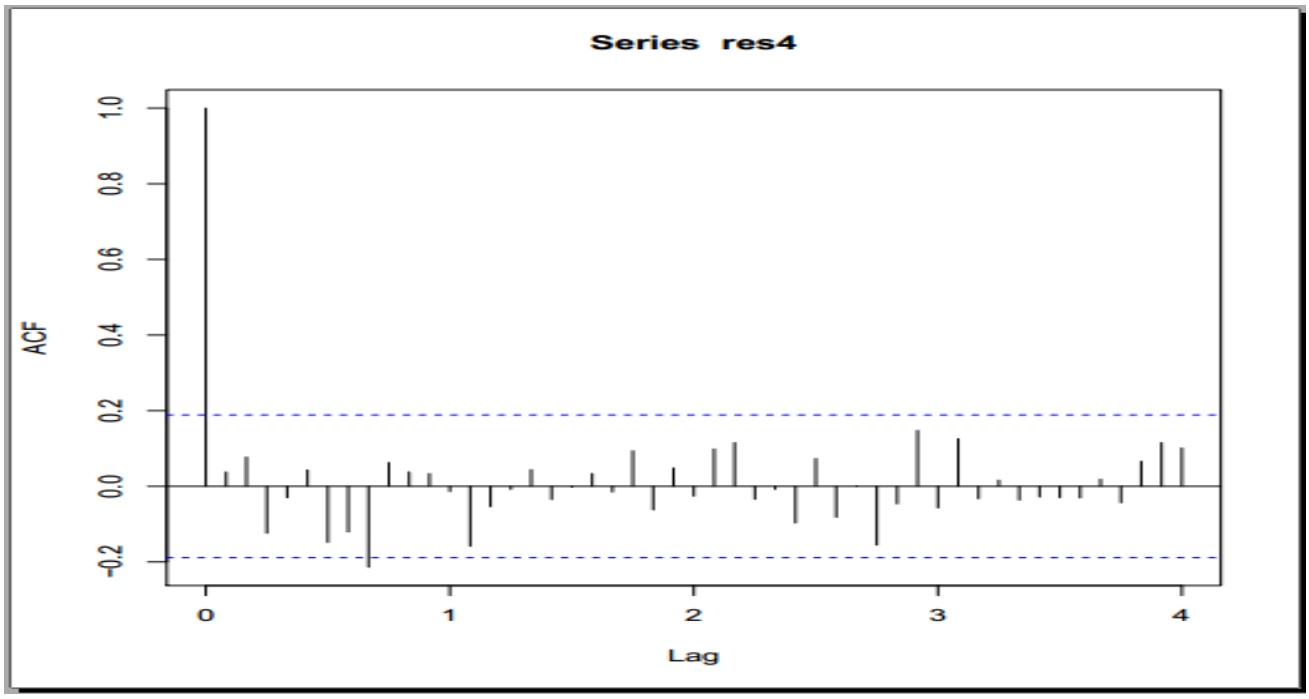


Figure 33: Residual ACF Plot (Typhoid fever period two)

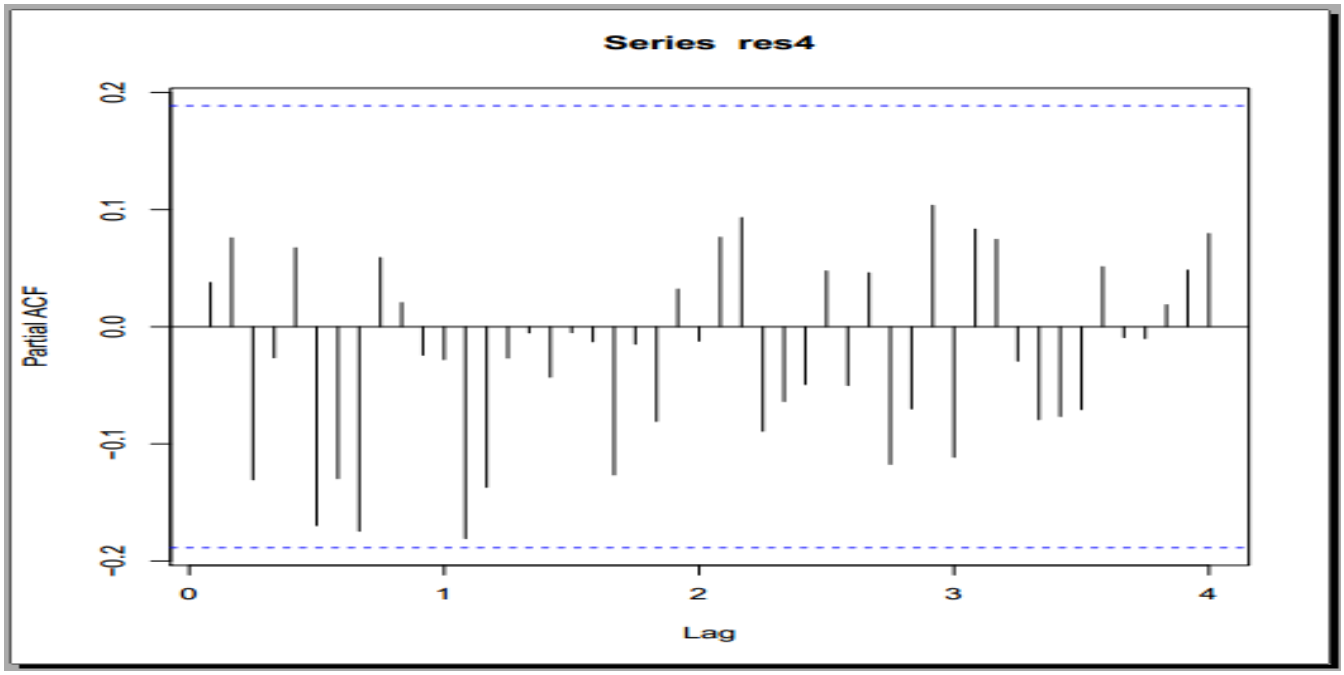


Figure 34: Residual PACF Plot (Typhoid fever period two)

The Q-Q plots of the residuals are presented in figure 35 and figure 36. The Q-Q plots of the residuals show that the residuals are approximately normally distributed.

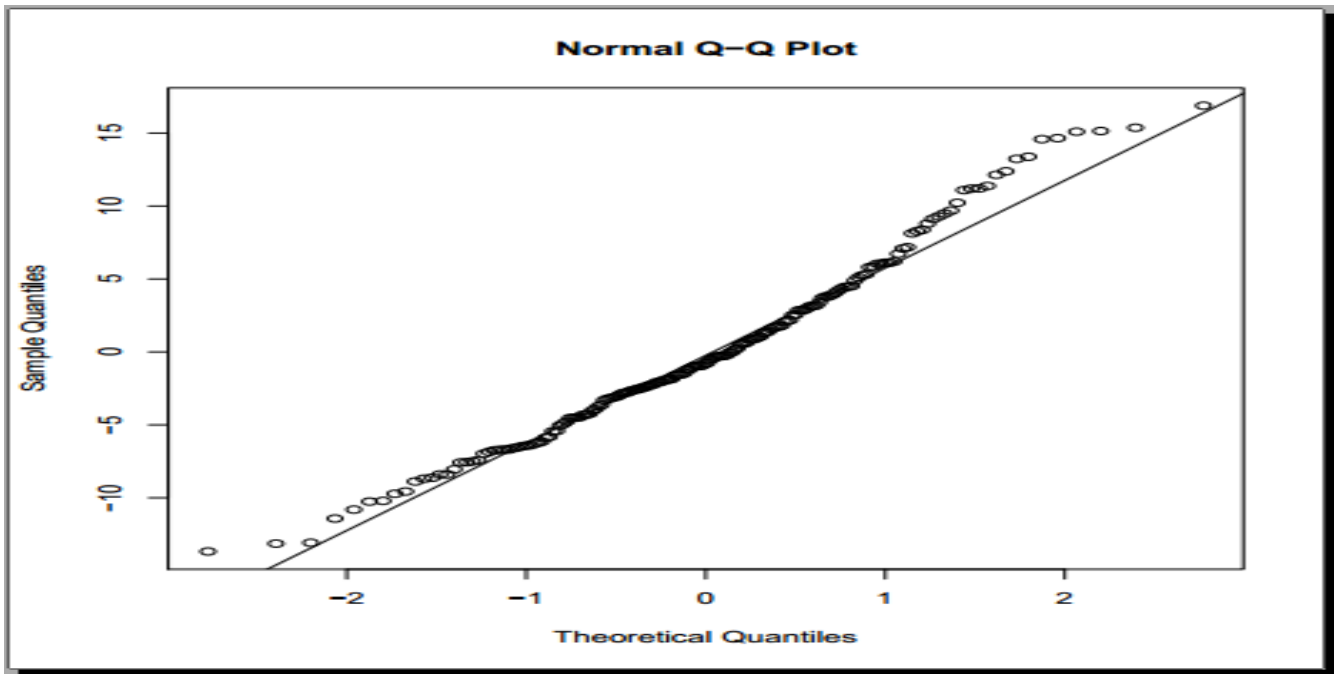


Figure 35: Residual Q-Q Plot (Malaria cases)

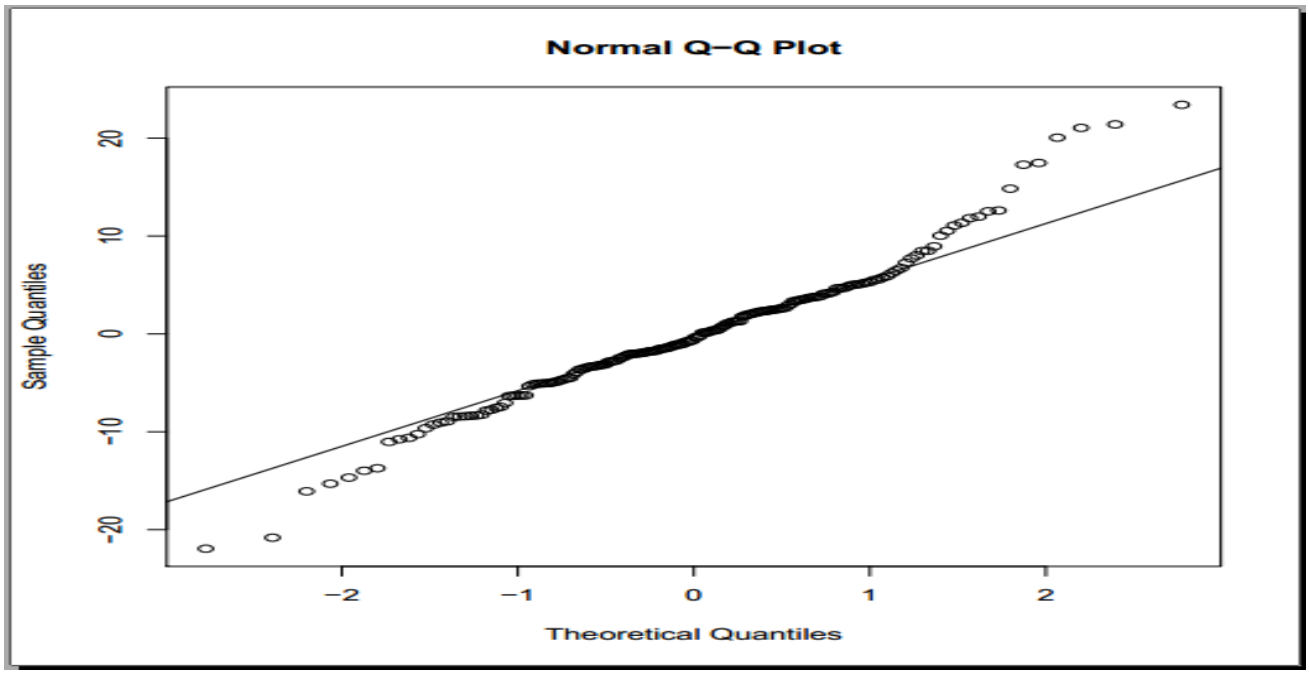


Figure 36: Residual Q-Q Plot (Typhoid fever)

**Ljung Box test (Malaria)**

**Malaria cases period one**

Box Q statistic = 0.1568, df = 1, p-value = 0.6921

The Ljung Box test shows that SARIMA (0,0,0) (1,1,0)[12] with drift model is adequate for describing the behavior and spread of malaria cases over period one in the region.

**Malaria cases period two**

Box Q statistic = 0.0713, df = 1, p-value = 0.7894

The Ljung Box test shows that SARIMA (1,0,1) (1,1,0) [12] model is adequate for describing the behavior and spread of malaria cases over period two in the region.

**Ljung Box test (Typhoid fever)**

**Typhoid fever period one**

Box Q statistic = 0.000, df = 1p-value = 0.9946

The Ljung Box test shows that SARIMA (2,0,0) (1,1,0) [12] model is adequate for describing the behavior and spread of typhoid fever over period one in region.

**Typhoid fever period two**

Box Q statistic = 0.1543, df = 1, p-value = 0.6944

The Ljung Box test shows that SARIMA (1,0,0) (1,1,0) [12] model is adequate for describing the behavior and spread of typhoid fever over period two in region.

The Ljung Box plots for all the models are presented in figure 37 to figure 40 below. The plots show that the models are adequate since all the p-values are above 0.05

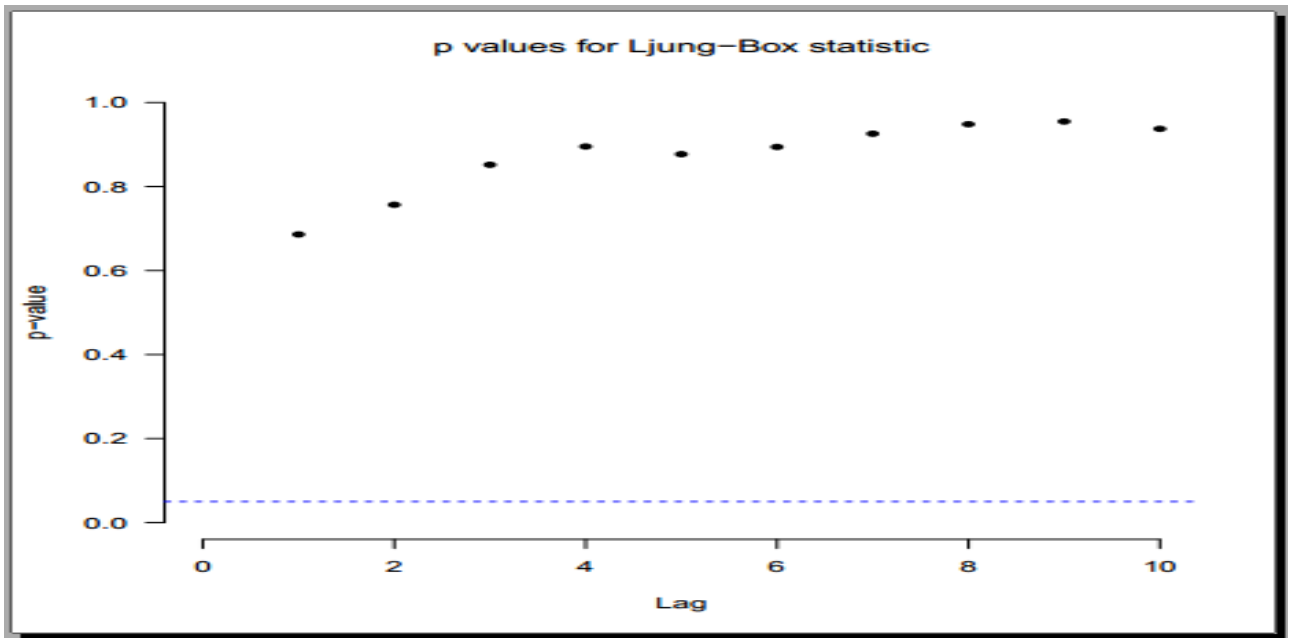


Figure 37: Ljung Box plot (Malaria cases period one)

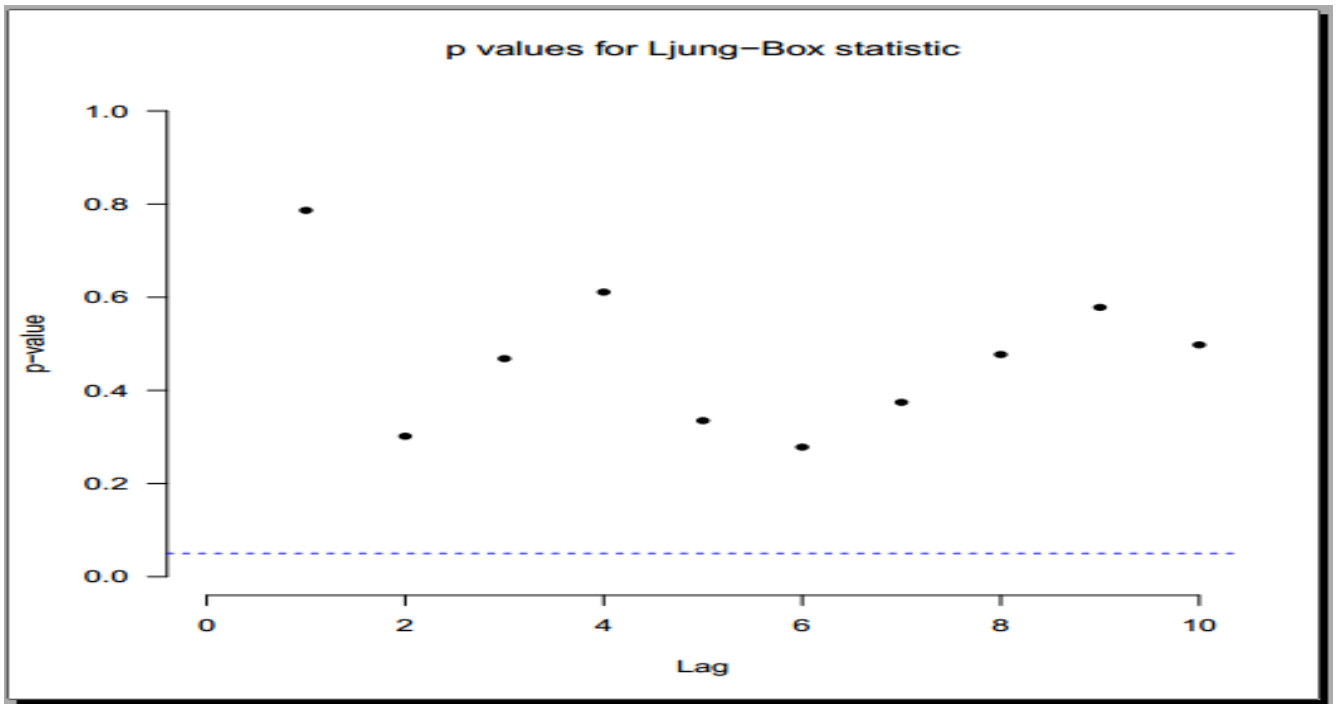


Figure 38: Ljung Box plot (Malaria cases period two)

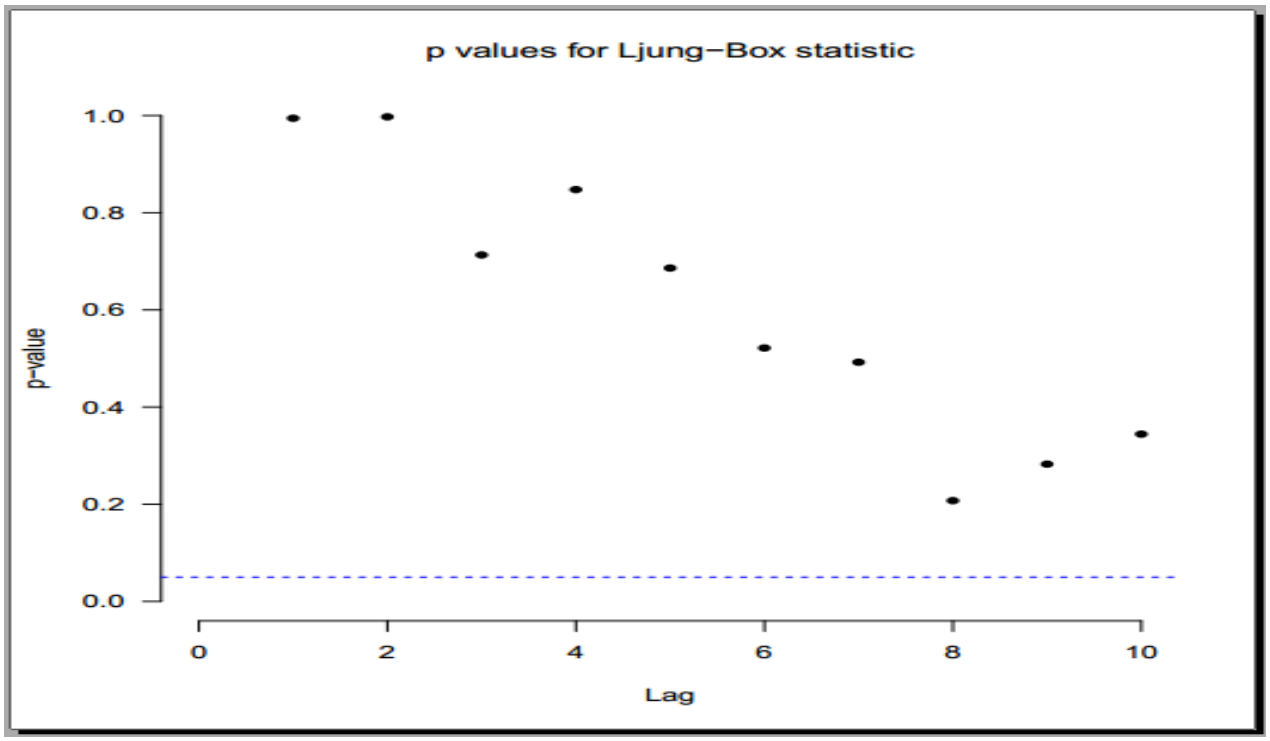


Figure 39: Ljung Box plot (Typhoid fever period one)

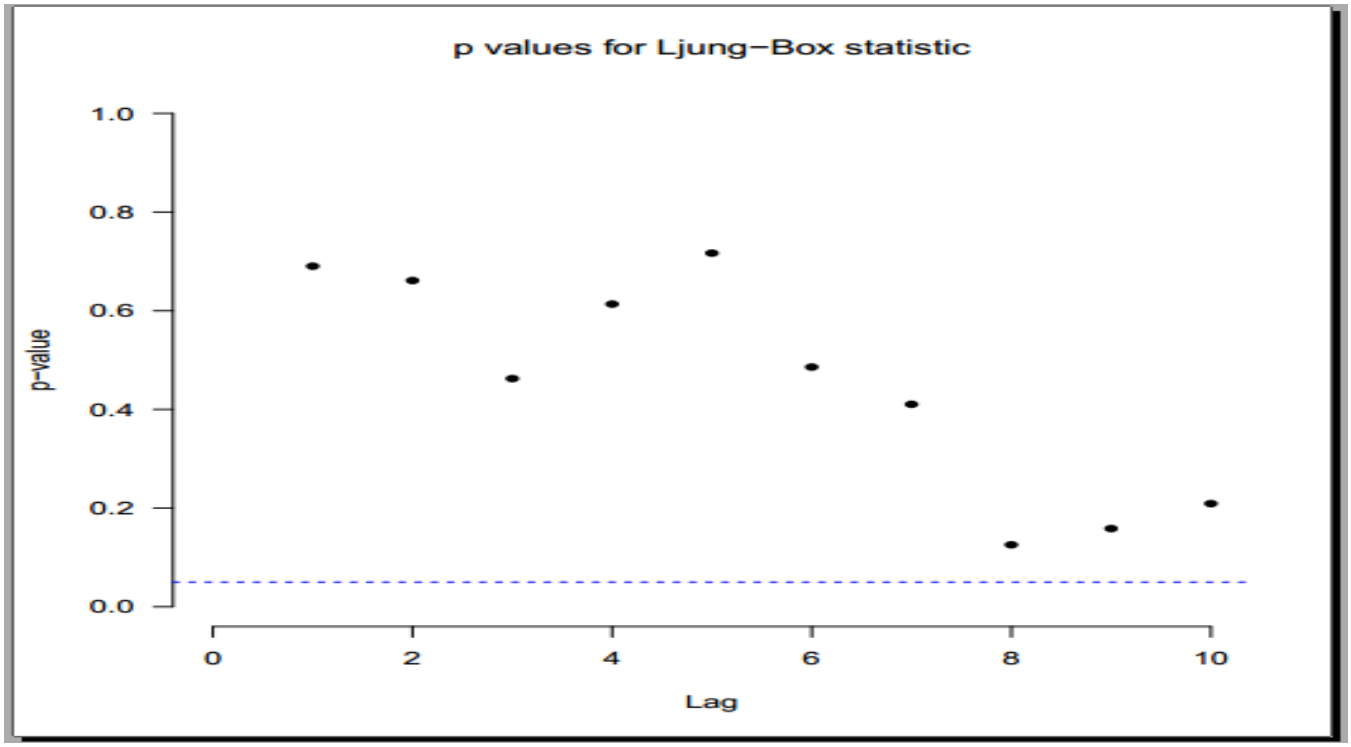


Figure 40: Ljung Box plot (Typhoid fever period two)

### 3.3 Forecast

All the models have been proven to be adequate based on the Ljung Box test and Ljung Box plots, we therefore go ahead to use the period two models in forecasting future prevalence of malaria and typhoid fever for 2018. The period two models were used for forecasting the future incidence of malaria and typhoid fever because the period gives recent information compared to period one. The mean, naïve, seasonal naïve and drift methods are presented in figure 41 and figure 42 for malaria and typhoid respectively as starting point. The mean, naïve and drift methods indicated that the incidence of malaria and typhoid fever will be constant in 2018 in the region. In application, this is not so as historical data shows that the incidence of malaria and typhoid fever varies at different period of the year. However, the seasonal naïve method presented more realistic forecast.

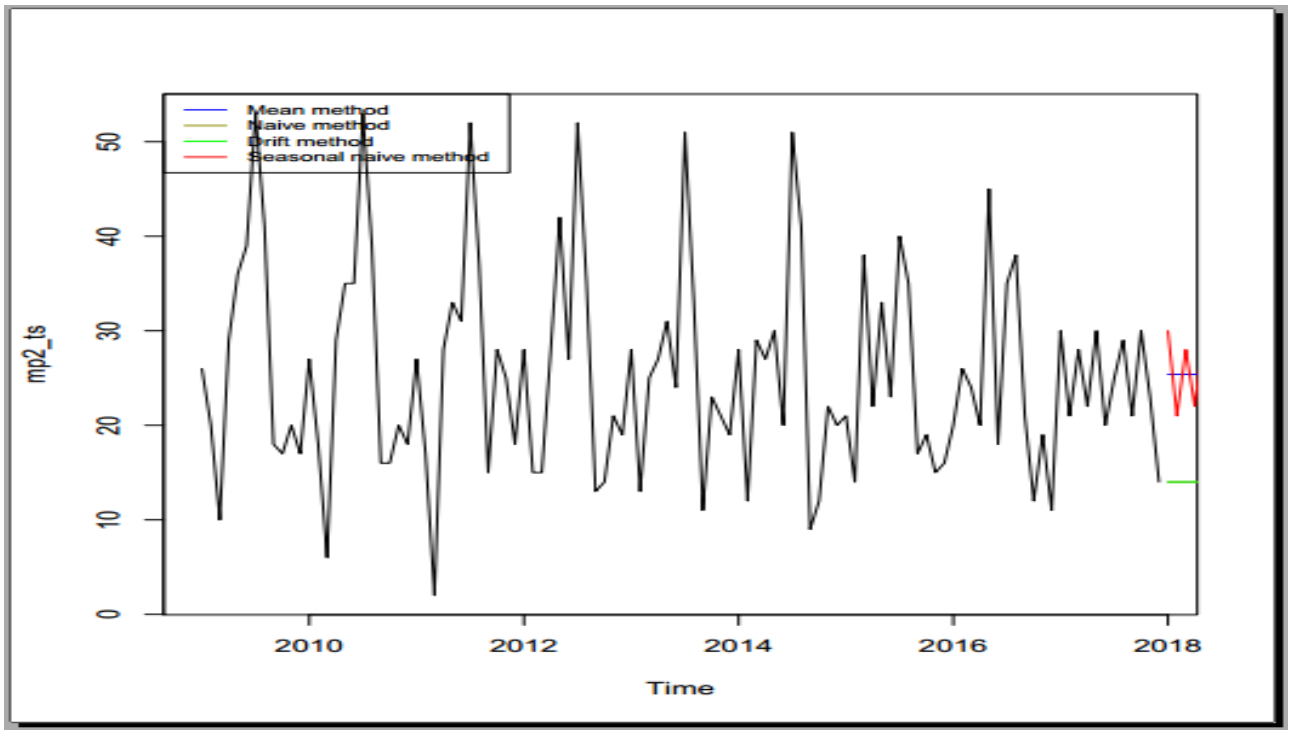


Figure 41: Mean, Naïve, Seasonal Naïve and Drift Naïve Method (Malaria cases)

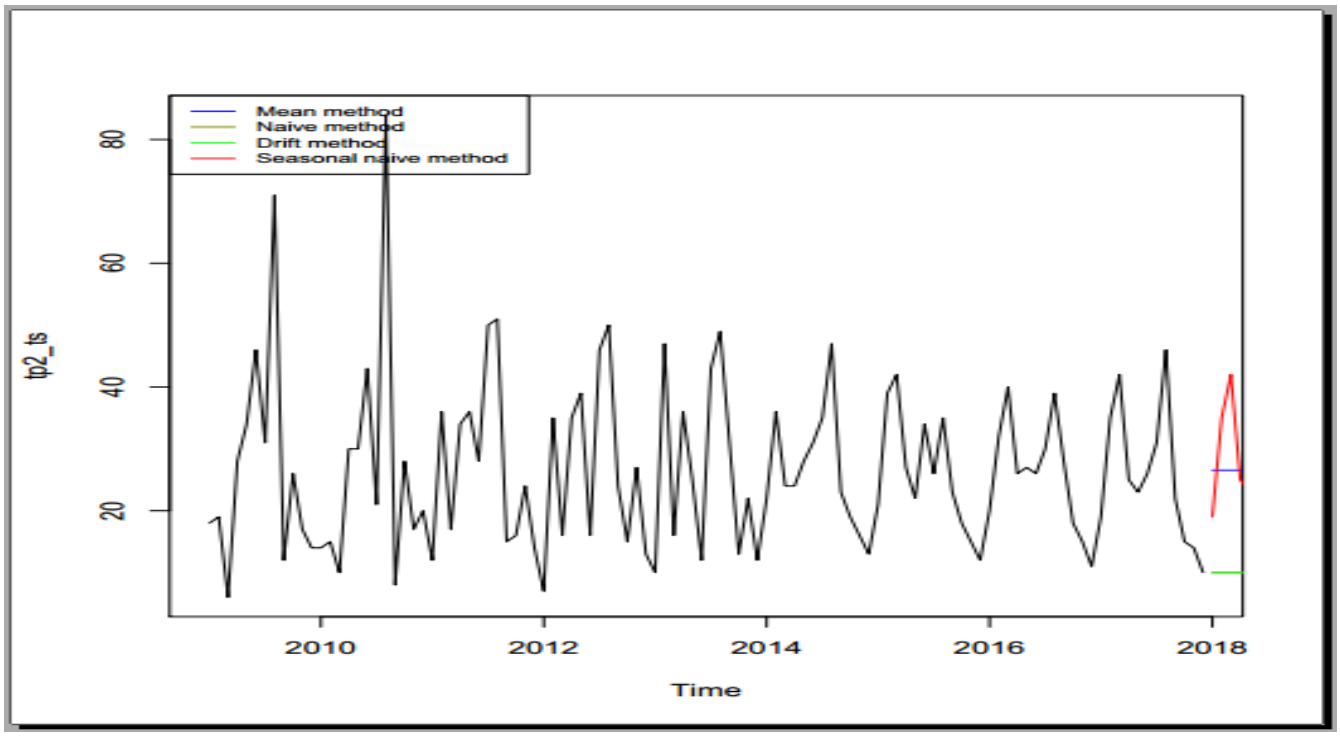


Figure 42: Mean, Naïve, Seasonal Naïve and Drift Naïve Method (Typhoid fever)

Therefore, the seasonal method was used to forecast future incidence of malaria and typhoid fever in the region. The plots for the forecast of both malaria and typhoid fever are presented in figure 43 and figure 44 respectively.

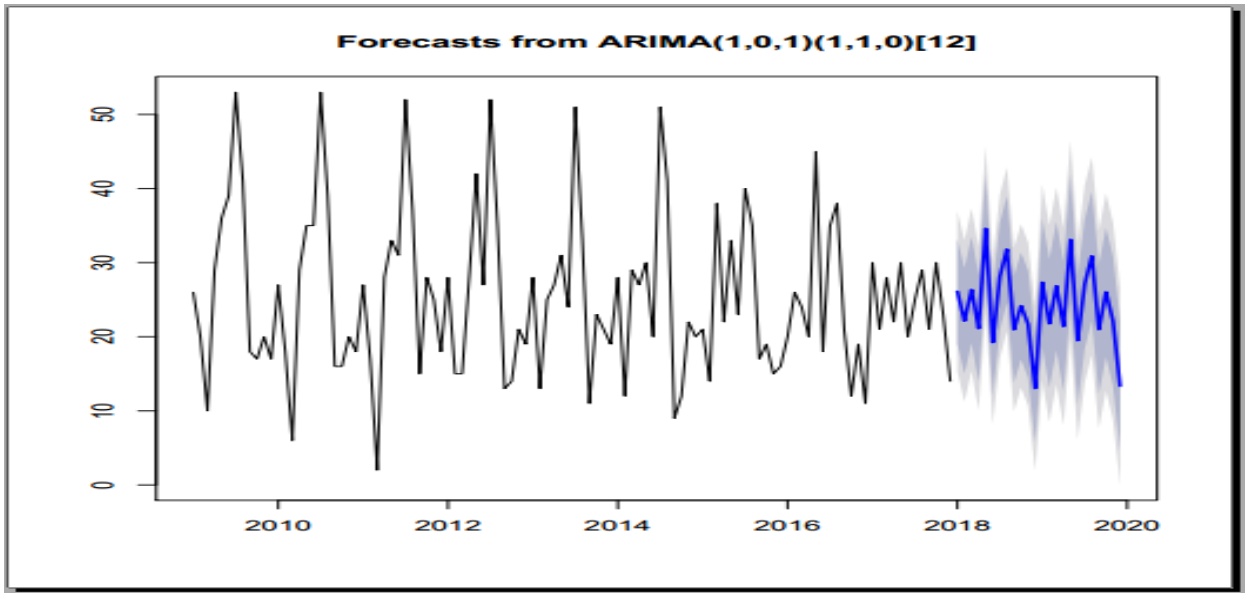


Figure 43: Plot of the forecasted Malaria cases

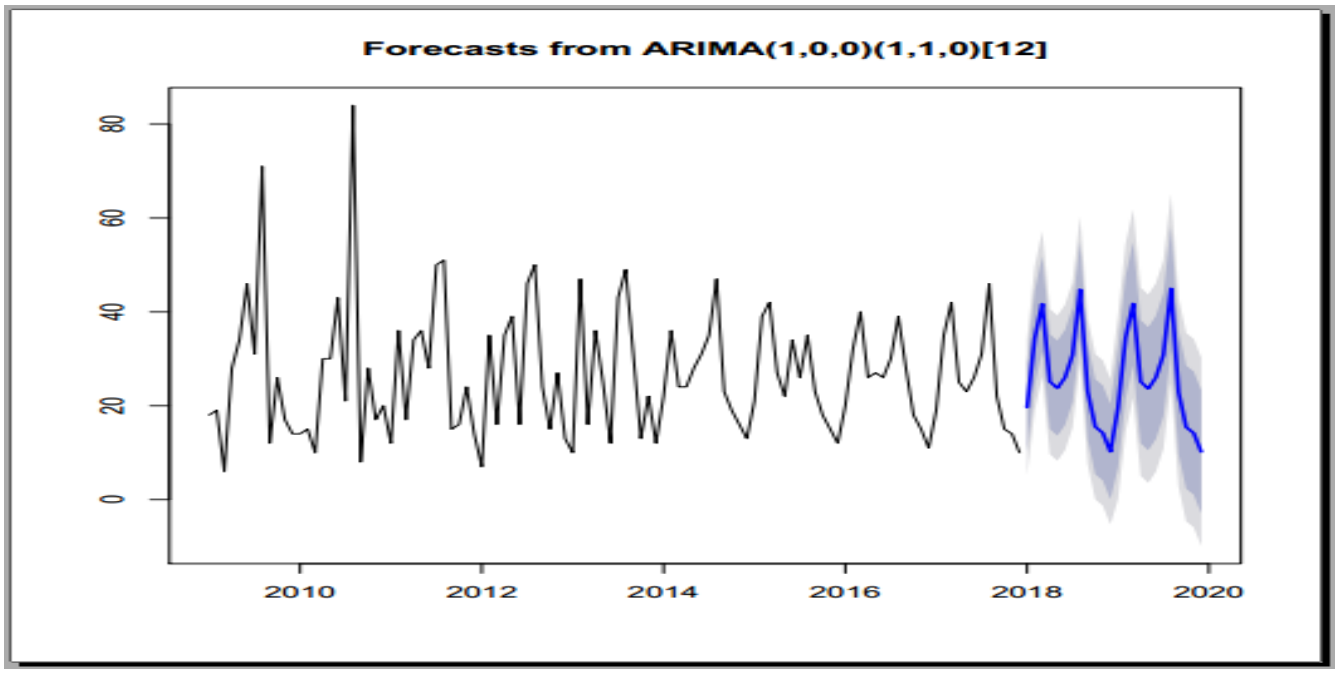


Figure 44: Plot of the forecasted Typhoid fever

The forecast values for both malaria and typhoid fever for the year 2018 are presented in table 2.

Table 2: Future Incidence of Malaria and Typhoid Fever (2018)

| Month | Malaria Incidence | Typhoid Incidence |
|---|---|---|
| January | 26.13 | 19.61 |
| February | 22.12 | 34.31 |
| March | 26.36 | 41.71 |
| April | 21.1 | 25.15 |
| May | 34.62 | 23.71 |
| June | 19.22 | 26.00 |
| July | 28.11 | 30.82 |
| August | 31.81 | 44.78 |
| September | 20.95 | 23.05 |

| | | |
|---|---|---|
| October | 24.19 | 15.52 |
| November | 21.69 | 14.17 |
| December | 13.02 | 10.17 |
| Total | 289.32 | 309 |

The forecast obtained from this work was compared with the actual reported cases for 2018 and presented in table 3.

Table 3: Actual versus Predicted cases of Malaria and Typhoid Fever (2018)

| Month | Actual Malaria Cases for 2018 | Predicted Malaria Cases for 2018 | Actual Typhoid Fever Cases for 2018 | Predicted Typhoid Fever Cases for 2018 |
|---|---|---|---|---|
| January | 25 | 26.13 | 20 | 19.61 |
| February | 21 | 22.12 | 35 | 34.31 |
| March | 24 | 26.36 | 39 | 41.71 |
| April | 20 | 21.1 | 27 | 25.15 |
| May | 32 | 34.62 | 21 | 23.71 |
| June | 21 | 19.22 | 25 | 26.00 |
| July | 27 | 28.11 | 32 | 30.82 |
| August | 30 | 31.81 | 45 | 44.78 |
| September | 22 | 20.95 | 21 | 23.05 |
| October | 26 | 24.19 | 17 | 15.52 |
| November | 19 | 21.69 | 15 | 14.17 |
| December | 11 | 13.02 | 9 | 10.17 |
| Total | 278 | 289.32 | 306 | 309 |

278 cases of malaria were reported in the region for the year 2018 while 289 cases of malaria were predicted for the region in 2018. 306 cases of typhoid fever were reported in the region for the year

2018 while 309 cases of typhoid fever were predicted for the region in 2018. The actual and predicted cases of both malaria and typhoid fever are presented in figures 45 and 46.

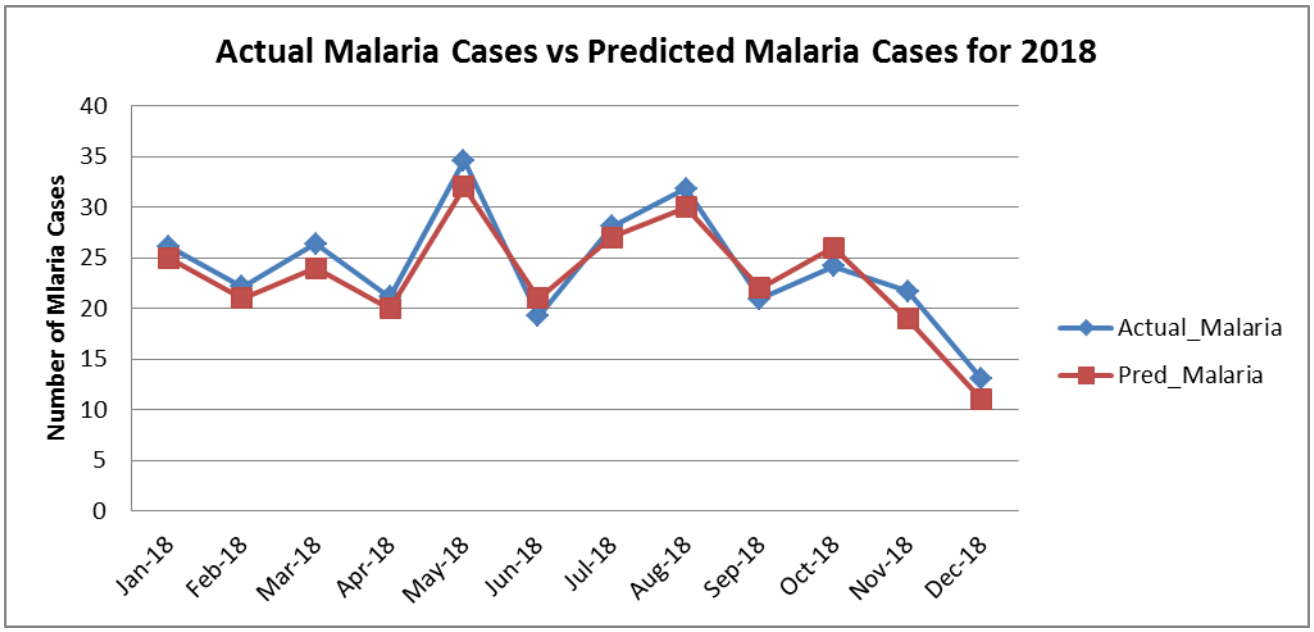


Figure 45: Actual Malaria Cases vs Predicted Malaria Cases for 2018

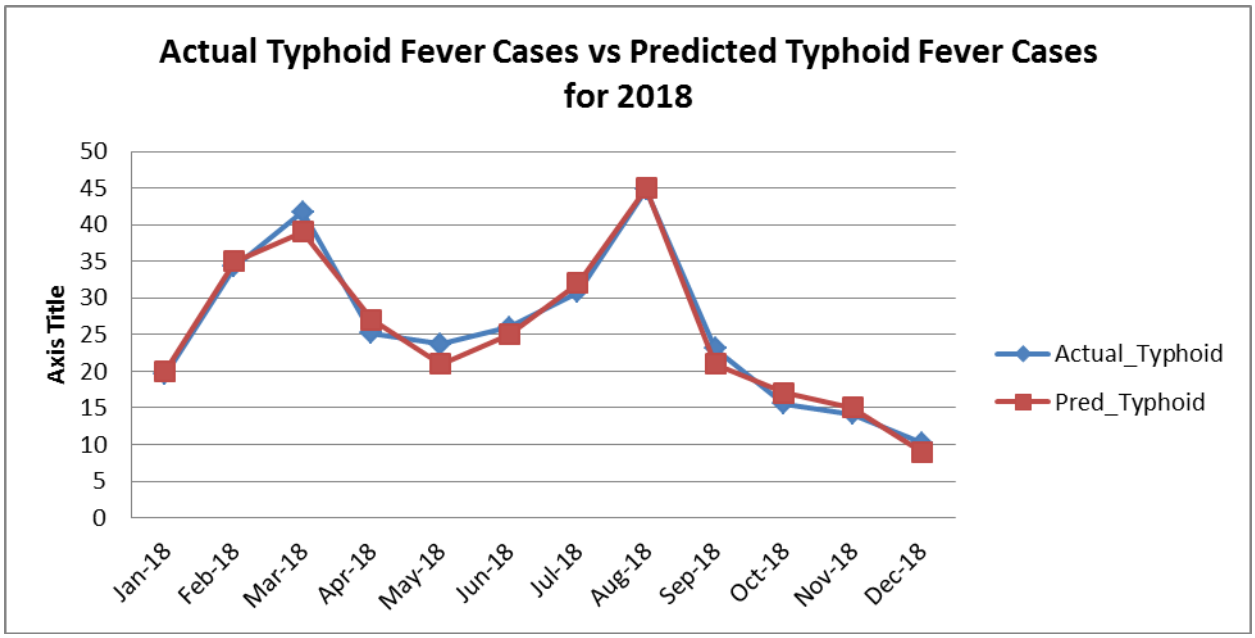


Figure 46: Actual Typhoid Fever Cases vs Predicted Typhoid Fever Cases for 2018

### 3.4 Chi-Square Test

Table 4 below presents the contingency table from which the chi-square test statistic will be computed.

Table 4: Contingency table for the gender and diseases

| Gender | Disease | |
|---|---|---|
| | Malaria cases | Typhoid fever |
| Male | 2069 | 2083 |
| Female | 2331 | 2379 |

The result obtained is presented below:

$\chi^2$ =0.748707

Df = 1

p-value = 0.3869

**Hypothesis to be tested**

$H_o$= There is no significant association between the gender and diseases

$H_1$= There is significant association between the gender and diseases

Since p-value = 0.3869 is greater than 0.05, we do not reject the null hypothesis and conclude that there is no significant association between the gender and diseases. This result indicates that the occurrence of the diseases is independent of the gender and both genders are susceptible to the diseases.

## 3.5 Correlation Analysis

The correlation between two variables tends to measure the strength of the relationship that exists between the two variables. There is a strong relationship between the two feverish conditions with malaria having more chances of causing fever compared to typhoid infection (Ukaegbu et al. 2014). The scatter diagram of malaria and typhoid fever is presented in figure 47 below. Also, figures 48 to 51 show the movement of both diseases over the period of study. The trend line indicates a positive relationship between the number of malaria cases and typhoid fever.

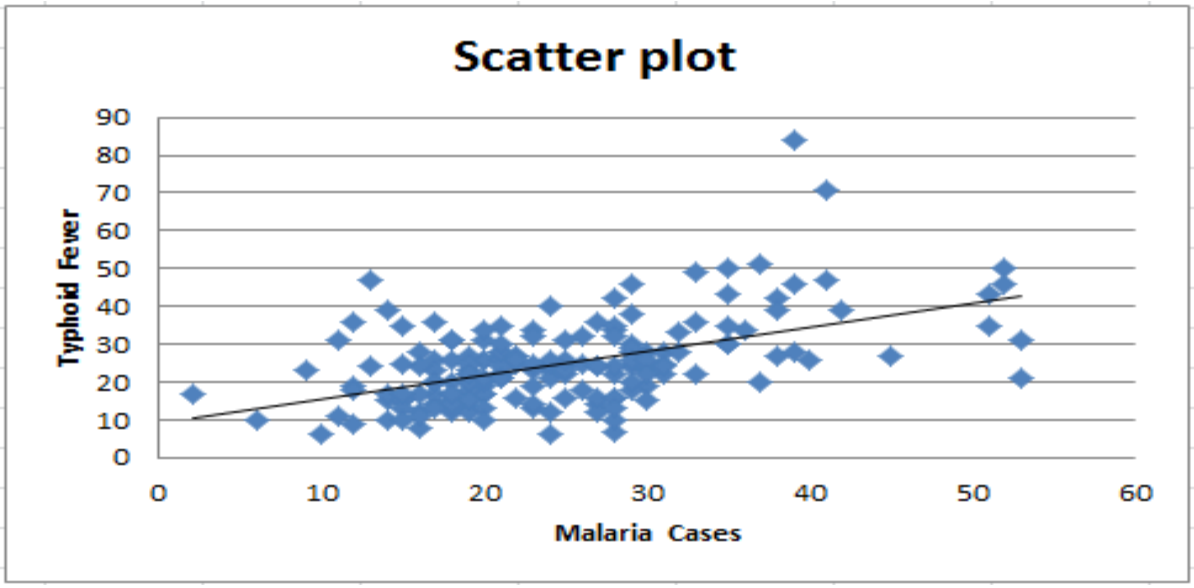


Figure 47: Scatter plot of Malaria and Typhoid

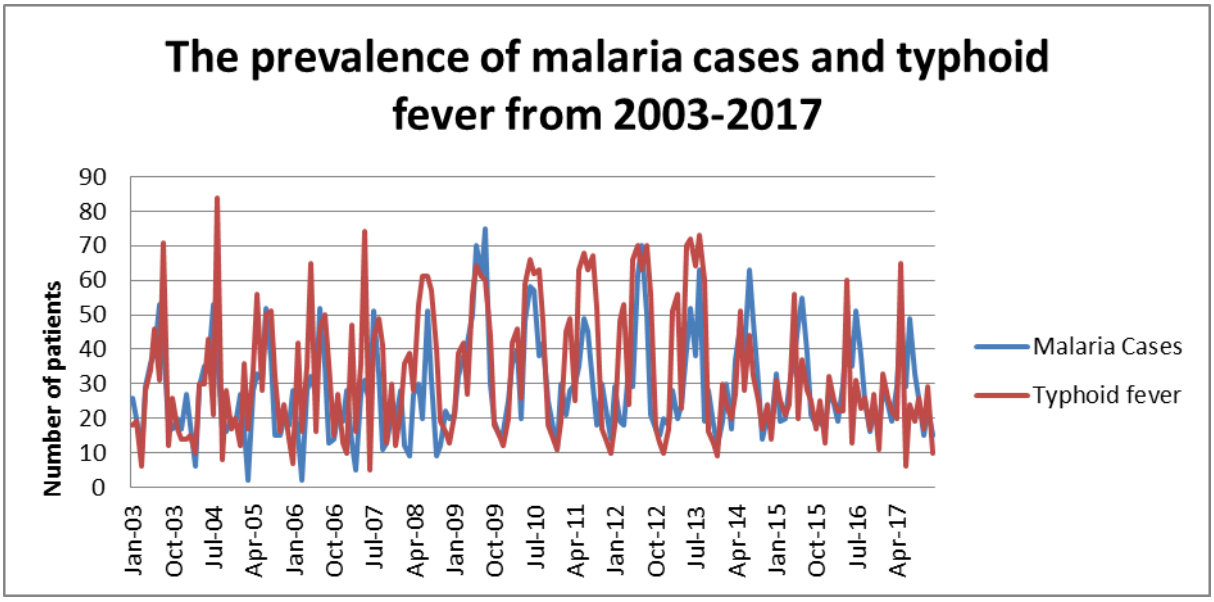


Figure 48: Malaria cases and Typhoid fever from 2003-2017

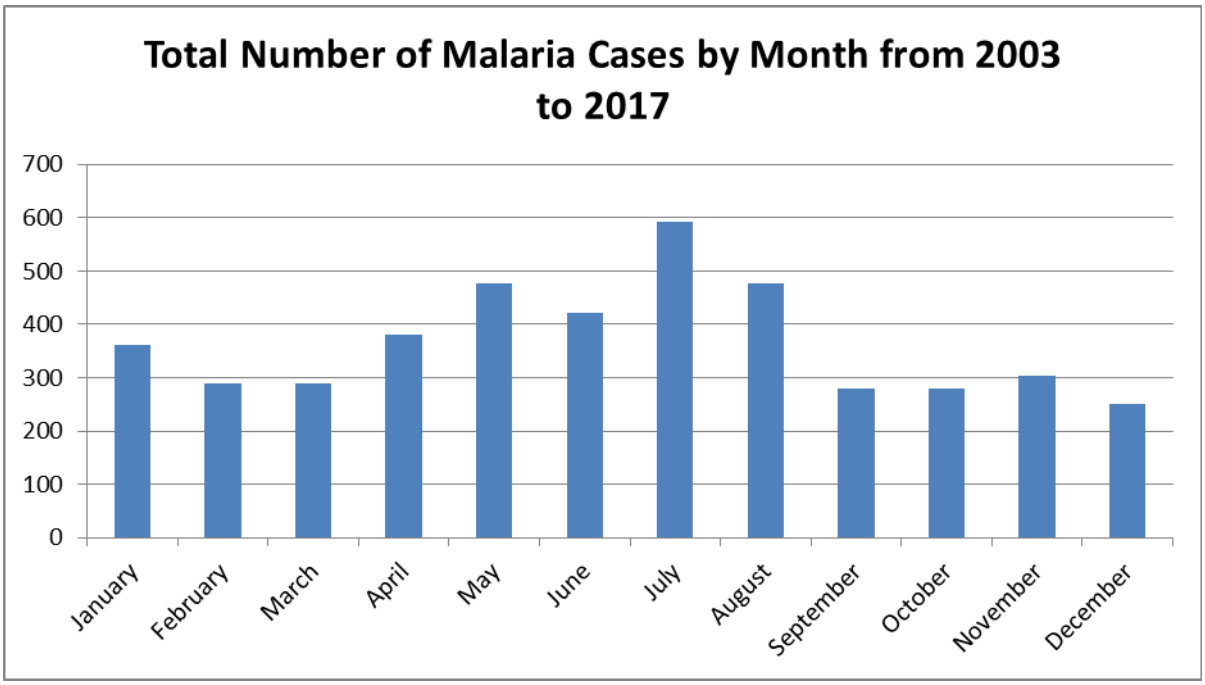


Figure 49: Total Number of Malaria Cases by Month from 2003 to 2017

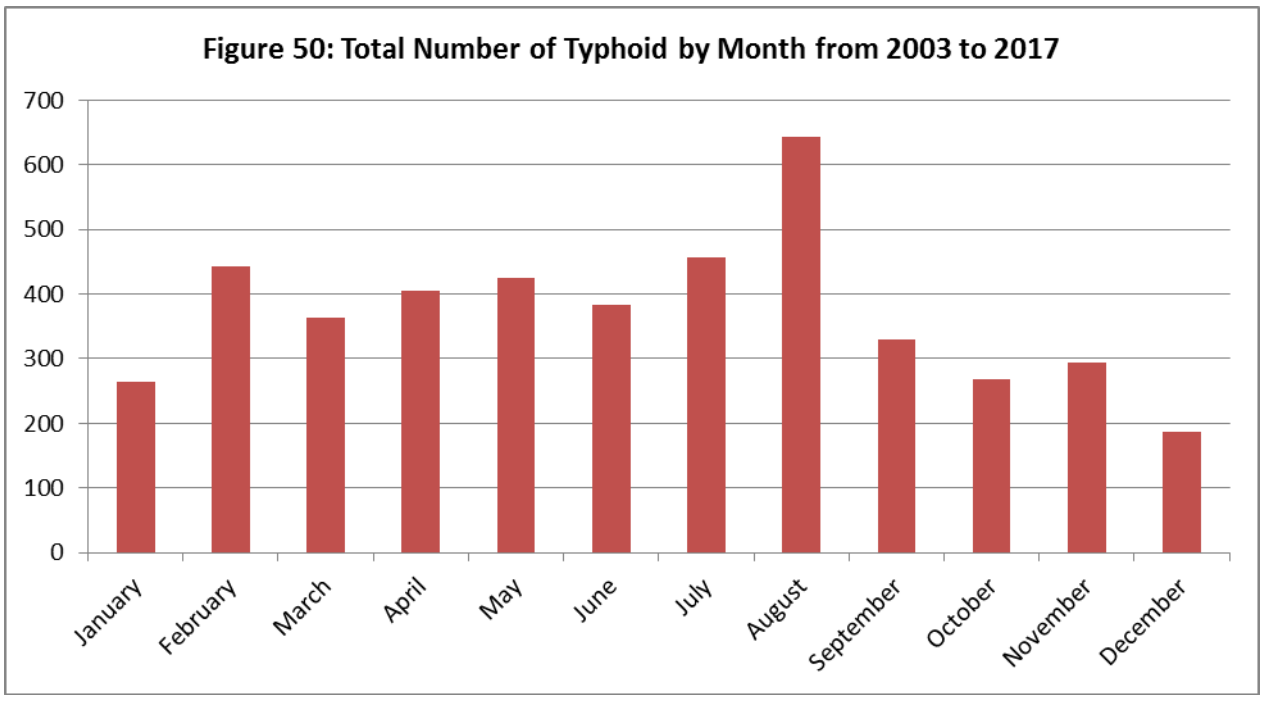


Figure 50: Total Number of Typhoid by Month from 2003 to 2017

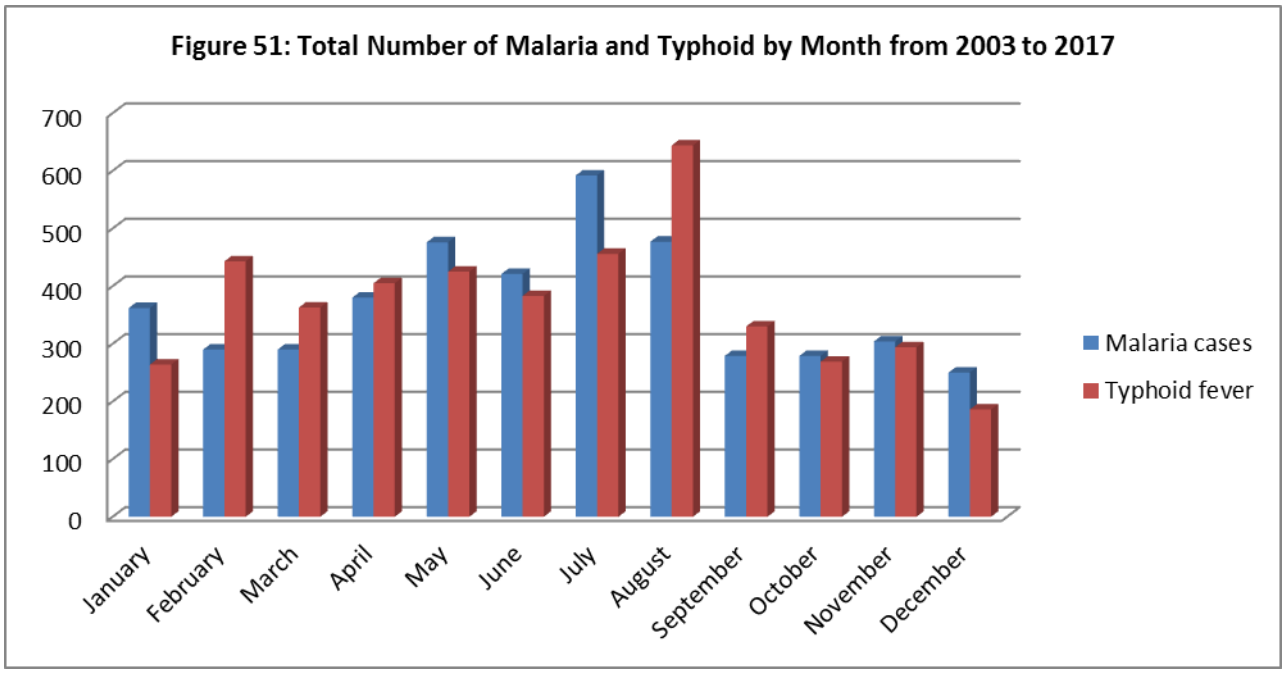


Figure 51: Total Number of Malaria and Typhoid by Month from 2003 to 2017

Using the correlation coefficient defined as

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{(n\sum x_i^2 - (\sum x_i)^2)(n\sum y_i^2 - (\sum y_i)^2)}}$$

where,

$n = 180$

$\sum x_i = 4400$

$\sum y_i = 4462$

$\sum x_i y_i = 118700$

$\sum x_i^2 - 122748$

$\sum y_i^2 = 133224$

$$r_{xy} = \frac{180(118700) - (4400)(4462)}{\sqrt{(180(122748) - (4400)^2)(180(133224) - (4462)^2)}}$$

$$r_{xy} = 0.518$$

Based on the data, we obtained the correlation coefficient between the malaria cases and typhoid fever to be 0.518. This implies that there is a positive relationship between malaria cases and typhoid fever in the region. It is expected that when there is an increase in the number of cases in one of the disease, there will also be increase in the number of cases of the other disease. A similar study, Ukaegbu et al.

(2014) showed that there is a strong relationship between malaria cases and typhoid fever. This result show that 100% increase in the malaria cases is associated with 51.8% increase in the typhoid fever cases and vice versa. The consequence of this is that there is relationship between malaria cases and typhoid fever in the region and there is tendency of a patient with one of the diseases coming up with the symptoms of the other disease.

# CHAPTER FOUR

# CONCLUSIONS AND RECOMENDATIONS

## 4.1 Conclusions

The results of this study indicated a downward trend in the number of malaria cases over the period under study. A decrease was observed in the number of malaria cases between 2011 to 2013 and 2016 to 2017. However, a slight increase was observed between 2014 and 2015. A downward trend in the malaria cases is expected in 2018 based on the fitted trend line. For the number of typhoid fever, a decrease was observed from 2012 to 2017 with the downward trend expected to continue in 2018 based on the fitted trend line.

The results of this study show that incidence of malaria and typhoid fever are affected or influenced by seasonal factors. Considering the period under study (2003 – 2017), the highest and lowest occurrence of malaria cases were reported in July (592) and December (250) respectively while the highest and lowest cases of typhoid fever were reported in August (644) and December (186) respectively.

The seasonal pattern observed in both the malaria and typhoid fever varied across two periods which are period one (2003 to 2008) and period two (2009 to 2017). Using arima model to study the components influencing the malaria and typhoid fever incidence in both period one and period two, SARIMA (0,0,0)(1,1,0)[12] with drift and SARIMA (1,0,1)(1,1,0)[12]were identified as the best model to describe the pattern of the incidence of malaria for period one and period two respectively while SARIMA (2,0,0)(1,1,0)[12] and SARIMA (1,0,0)(1,1,0)[12] typhoid fever were identified as the best model to describe the pattern of the incidence of typhoid fever for period one and period two respectively. The identified models for period two for both malaria and typhoid fever were used to forecast future occurrence taking into consideration the seasonal factor and trend influencing the incidence of malaria and typhoid fever in the region. The forecast made in this study shows that there will be a slight increase in the number of malaria cases which will be followed by a decrease with high occurrence expected around May to August 2018. The lowest cases are expected in December 2018. The projection for the typhoid fever in the year 2018 also shows some fluctuations with high cases expected around March to August 2018. Lower occurrence is expected around October to December 2018.Evidence from the data shows that there is no significant association between the gender and diseases based on the chi-square test of association. The implication of this result is that both male and female are susceptible to both diseases. The degree of relationship between malaria and typhoid was obtained using correlation coefficient. Based on the data, the correlation coefficient obtained was approximately 0.52 implying that there are about 52% chances of a patient with one of the diseases to

be affected with the other. The total number of malaria cases expected in 2018 is approximately 290while the total number of typhoid fever expected in 2018 is approximately 305.

## 4.2 Recommendations

It is evident from the historical data used in this research and the results obtained that the incidence of malaria and typhoid fever is influenced or affected by seasonal factors as the incidence of malaria and typhoid fever tends to be high at some period of the year and low at some other period. Proper enlightenment program is recommended across gender to enlighten the people of the region about the seasonal pattern and educate them on preventive measures especially at the period where high incidence is expected. Evidence from the data shows that there is positive correlation between the malaria cases and typhoid fever. Further research is needed to determine the factors responsible for the high and low incidence at different periods of the year in the region.

# CHAPTER FIVE

# LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

## 5.1 Limitations

One important limitation identified in this research is the unavailability of comprehensive and accurate data from the six geopolitical regions of Nigeria. This limits the scope of this study as comparison could not be made among the states or geopolitical zones. Also, conclusions could not be made on the association between the ages of the patients and the two diseases.

## 5.2 Recommendations for Future Work

Future studies on the trend and spread of the diseases across the geopolitical regions are required to determine which region is more susceptible to the diseases and measures required to curb the trend.

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## 7.0 APPENDIX

**Table A1: Reported Cases of Malaria between 2003 and 2017**

| Month/Year | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| January | 26 | 27 | 27 | 28 | 28 | 28 | 21 | 20 | 30 | 29 | 18 | 19 | 29 | 17 | 15 |
| February | 20 | 18 | 17 | 15 | 13 | 12 | 14 | 26 | 21 | 19 | 18 | 30 | 19 | 24 | 24 |
| March | 10 | 6 | 2 | 15 | 25 | 29 | 38 | 24 | 28 | 18 | 20 | 17 | 20 | 19 | 19 |
| April | 29 | 29 | 28 | 28 | 27 | 27 | 22 | 20 | 22 | 30 | 24 | 19 | 16 | 30 | 29 |
| May | 36 | 35 | 33 | 42 | 31 | 30 | 33 | 45 | 30 | 29 | 26 | 23 | 30 | 21 | 32 |
| June | 39 | 35 | 31 | 27 | 24 | 20 | 23 | 18 | 20 | 32 | 24 | 39 | 37 | 28 | 24 |
| July | 53 | 53 | 52 | 52 | 51 | 51 | 40 | 35 | 25 | 28 | 38 | 31 | 25 | 31 | 27 |
| August | 41 | 39 | 37 | 35 | 33 | 41 | 35 | 38 | 29 | 29 | 23 | 28 | 21 | 25 | 23 |
| September | 18 | 16 | 15 | 13 | 11 | 9 | 17 | 21 | 21 | 21 | 19 | 30 | 21 | 25 | 22 |
| October | 17 | 16 | 28 | 14 | 23 | 12 | 19 | 12 | 30 | 17 | 28 | 14 | 18 | 16 | 15 |
| November | 20 | 20 | 25 | 21 | 21 | 22 | 15 | 19 | 23 | 15 | 18 | 21 | 19 | 22 | 23 |
| December | 17 | 18 | 18 | 19 | 19 | 20 | 16 | 11 | 14 | 20 | 12 | 18 | 17 | 16 | 15 |
| Total | 326 | 312 | 313 | 309 | 306 | 301 | 293 | 289 | 293 | 287 | 268 | 289 | 272 | 274 | 268 |

Table A2: Reported cases of typhoid fever between 2003 and 2017

| Month/Year | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **January** | 18 | 14 | 12 | 7 | 10 | 22 | 21 | 20 | 19 | 18 | 17 | 15 | 26 | 20 | 25 |
| **February** | 19 | 15 | 36 | 35 | 47 | 36 | 39 | 32 | 35 | 20 | 31 | 24 | 23 | 25 | 26 |
| **March** | 6 | 10 | 17 | 16 | 16 | 24 | 42 | 40 | 42 | 31 | 34 | 20 | 21 | 22 | 22 |
| **April** | 28 | 30 | 34 | 35 | 36 | 24 | 27 | 26 | 25 | 24 | 23 | 27 | 24 | 22 | 20 |
| **May** | 34 | 30 | 36 | 39 | 25 | 28 | 22 | 27 | 23 | 29 | 25 | 23 | 26 | 30 | 28 |
| **June** | 46 | 43 | 28 | 16 | 12 | 31 | 34 | 26 | 26 | 33 | 21 | 28 | 20 | 13 | 6 |
| **July** | 31 | 21 | 50 | 46 | 43 | 35 | 26 | 30 | 31 | 24 | 27 | 22 | 22 | 24 | 24 |
| **August** | 71 | 84 | 51 | 50 | 49 | 47 | 35 | 39 | 46 | 38 | 32 | 32 | 28 | 23 | 19 |
| **September** | 12 | 8 | 15 | 24 | 31 | 23 | 23 | 28 | 22 | 26 | 20 | 25 | 21 | 26 | 26 |
| **October** | 26 | 28 | 16 | 15 | 13 | 19 | 18 | 18 | 15 | 17 | 16 | 17 | 17 | 17 | 17 |
| **November** | 17 | 17 | 24 | 27 | 22 | 16 | 15 | 15 | 14 | 13 | 13 | 24 | 25 | 27 | 25 |
| **December** | 14 | 20 | 14 | 13 | 12 | 13 | 12 | 11 | 10 | 10 | 9 | 14 | 13 | 11 | 10 |
| **Total** | 322 | 320 | 333 | 323 | 316 | 318 | 314 | 312 | 308 | 283 | 268 | 271 | 266 | 260 | 248 |

Table A3: Gender Distribution of Malaria cases between 2003 and 2010

| Month/Year | 2003 | | 2004 | | 2005 | | 2006 | | 2007 | | 2008 | | 2009 | | 2010 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | F | M | F | M | F | M | F | M | F | M | F | M | F | M | F |
| **January** | 10 | 16 | 17 | 10 | 15 | 12 | 17 | 11 | 14 | 14 | 8 | 20 | 9 | 12 | 13 | 7 |
| **February** | 10 | 10 | 9 | 9 | 7 | 10 | 9 | 6 | 3 | 10 | 6 | 6 | 8 | 6 | 7 | 19 |
| **March** | 6 | 4 | 2 | 4 | 0 | 2 | 8 | 7 | 10 | 15 | 14 | 15 | 9 | 29 | 14 | 10 |
| **April** | 14 | 15 | 17 | 12 | 8 | 20 | 10 | 18 | 17 | 10 | 18 | 9 | 12 | 10 | 7 | 13 |
| **May** | 17 | 19 | 15 | 20 | 16 | 17 | 17 | 25 | 14 | 17 | 14 | 16 | 20 | 13 | 16 | 29 |
| **June** | 14 | 25 | 17 | 18 | 11 | 20 | 17 | 10 | 10 | 14 | 5 | 15 | 8 | 15 | 10 | 8 |
| **July** | 33 | 20 | 30 | 23 | 20 | 32 | 12 | 40 | 20 | 31 | 25 | 26 | 15 | 25 | 15 | 20 |
| **August** | 14 | 27 | 19 | 20 | 17 | 20 | 20 | 15 | 16 | 17 | 25 | 16 | 16 | 19 | 20 | 18 |
| **September** | 10 | 8 | 6 | 10 | 5 | 10 | 3 | 10 | 7 | 4 | 3 | 6 | 10 | 7 | 8 | 13 |
| **October** | 7 | 10 | 5 | 11 | 17 | 11 | 7 | 7 | 15 | 8 | 5 | 7 | 7 | 12 | 4 | 8 |
| **November** | 10 | 10 | 8 | 12 | 10 | 15 | 10 | 11 | 6 | 15 | 10 | 12 | 8 | 7 | 4 | 15 |
| **December** | 8 | 9 | 8 | 10 | 13 | 5 | 9 | 10 | 7 | 12 | 7 | 13 | 6 | 10 | 3 | 8 |
| **Total** | 153 | 173 | 153 | 159 | 139 | 174 | 139 | 170 | 139 | 167 | 140 | 161 | 128 | 165 | 121 | 168 |

Table A4: Gender Distribution of Malaria cases between 2011 and 2017

| Month/Year | 2011 | | 2012 | | 2013 | | 2014 | | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | F | M | F | M | F | M | F | M | F | M | F | M | F |
| **January** | 12 | 18 | 15 | 14 | 12 | 6 | 6 | 13 | 15 | 14 | 8 | 9 | 7 | 8 |
| **February** | 9 | 12 | 13 | 6 | 10 | 8 | 12 | 18 | 14 | 5 | 14 | 10 | 15 | 9 |
| **March** | 10 | 18 | 5 | 13 | 16 | 4 | 10 | 7 | 7 | 13 | 9 | 10 | 11 | 8 |
| **April** | 13 | 9 | 19 | 11 | 14 | 10 | 9 | 10 | 10 | 6 | 13 | 17 | 10 | 19 |
| **May** | 19 | 11 | 20 | 9 | 12 | 14 | 14 | 9 | 10 | 20 | 7 | 14 | 17 | 15 |
| **June** | 8 | 12 | 17 | 15 | 14 | 10 | 22 | 17 | 24 | 13 | 12 | 16 | 10 | 14 |
| **July** | 10 | 15 | 12 | 16 | 18 | 20 | 11 | 20 | 5 | 20 | 13 | 18 | 10 | 17 |
| **August** | 12 | 17 | 13 | 16 | 15 | 8 | 15 | 13 | 16 | 5 | 15 | 10 | 8 | 15 |
| **September** | 9 | 12 | 14 | 7 | 5 | 14 | 11 | 19 | 11 | 10 | 10 | 15 | 12 | 10 |
| **October** | 14 | 16 | 11 | 6 | 12 | 16 | 7 | 7 | 12 | 6 | 7 | 9 | 6 | 9 |
| **November** | 17 | 6 | 7 | 8 | 6 | 12 | 14 | 7 | 4 | 15 | 11 | 11 | 13 | 10 |
| **December** | 10 | 4 | 7 | 13 | 4 | 8 | 6 | 12 | 10 | 7 | 6 | 10 | 4 | 11 |
| **Total** | 143 | 150 | 153 | 134 | 138 | 130 | 137 | 152 | 138 | 134 | 125 | 149 | 123 | 145 |

Table A5: Gender Distribution Typhoid fever between 2003 and 2010

| Month/Year | 2003 | | 2004 | | 2005 | | 2006 | | 2007 | | 2008 | | 2009 | | 2010 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | F | M | F | M | F | M | F | M | F | M | F | M | F | M | F |
| **January** | 8 | 10 | 10 | 4 | 5 | 7 | 5 | 2 | 3 | 7 | 8 | 14 | 9 | 12 | 13 | 7 |
| **February** | 10 | 9 | 8 | 7 | 16 | 20 | 19 | 16 | 20 | 27 | 16 | 20 | 20 | 19 | 13 | 19 |
| **March** | 2 | 4 | 4 | 6 | 10 | 7 | 8 | 8 | 9 | 7 | 13 | 11 | 13 | 29 | 22 | 18 |
| **April** | 8 | 20 | 10 | 20 | 16 | 18 | 15 | 20 | 21 | 15 | 14 | 10 | 15 | 12 | 11 | 15 |
| **May** | 16 | 18 | 12 | 18 | 16 | 20 | 17 | 22 | 11 | 14 | 10 | 18 | 15 | 7 | 10 | 17 |
| **June** | 26 | 20 | 13 | 30 | 15 | 13 | 10 | 6 | 8 | 4 | 12 | 19 | 14 | 20 | 16 | 10 |
| **July** | 12 | 19 | 10 | 11 | 15 | 35 | 18 | 28 | 12 | 31 | 17 | 18 | 7 | 19 | 10 | 20 |
| **August** | 30 | 41 | 34 | 50 | 27 | 24 | 30 | 20 | 19 | 30 | 25 | 22 | 16 | 19 | 20 | 19 |
| **September** | 6 | 6 | 5 | 3 | 6 | 9 | 10 | 14 | 20 | 11 | 8 | 15 | 13 | 10 | 13 | 15 |
| **October** | 12 | 14 | 12 | 16 | 9 | 7 | 7 | 8 | 3 | 10 | 9 | 10 | 7 | 11 | 8 | 10 |
| **November** | 5 | 12 | 10 | 7 | 10 | 14 | 12 | 15 | 10 | 12 | 8 | 8 | 8 | 7 | 5 | 10 |
| **December** | 4 | 10 | 10 | 10 | 5 | 9 | 6 | 7 | 6 | 6 | 3 | 10 | 4 | 8 | 3 | 8 |
| **Total** | 139 | 183 | 138 | 182 | 150 | 183 | 157 | 166 | 142 | 174 | 143 | 175 | 141 | 173 | 144 | 168 |

Table A6: Gender Distribution Typhoid fever between 2011 and 2017

| Month/Year | 2011 | | 2012 | | 2013 | | 2014 | | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | F | M | F | M | F | M | F | M | F | M | F | M | F |
| **January** | 8 | 11 | 9 | 9 | 12 | 5 | 6 | 9 | 13 | 13 | 9 | 11 | 12 | 13 |
| **February** | 16 | 19 | 8 | 12 | 16 | 15 | 8 | 16 | 15 | 8 | 15 | 10 | 15 | 11 |
| **March** | 17 | 25 | 16 | 15 | 20 | 14 | 12 | 8 | 8 | 13 | 9 | 13 | 13 | 9 |
| **April** | 15 | 10 | 17 | 7 | 13 | 10 | 11 | 16 | 14 | 10 | 5 | 17 | 10 | 10 |
| **May** | 14 | 9 | 17 | 12 | 11 | 14 | 14 | 9 | 10 | 16 | 14 | 16 | 15 | 13 |
| **June** | 10 | 16 | 13 | 20 | 12 | 9 | 18 | 10 | 13 | 7 | 4 | 9 | 2 | 4 |
| **July** | 11 | 20 | 8 | 16 | 9 | 18 | 8 | 14 | 5 | 17 | 11 | 13 | 10 | 14 |
| **August** | 20 | 26 | 23 | 15 | 20 | 12 | 17 | 15 | 16 | 12 | 13 | 10 | 8 | 11 |
| **September** | 10 | 12 | 8 | 18 | 6 | 14 | 10 | 15 | 11 | 10 | 11 | 15 | 14 | 12 |
| **October** | 5 | 10 | 10 | 7 | 7 | 9 | 6 | 11 | 12 | 5 | 7 | 10 | 8 | 9 |
| **November** | 10 | 4 | 8 | 5 | 5 | 8 | 14 | 10 | 10 | 15 | 15 | 12 | 13 | 12 |
| **December** | 6 | 4 | 5 | 5 | 4 | 5 | 6 | 8 | 9 | 4 | 7 | 4 | 4 | 6 |
| **Total** | 142 | 166 | 142 | 141 | 135 | 133 | 130 | 141 | 136 | 130 | 120 | 140 | 124 | 124 |