TIME SERIES ANALYSIS OF REPORTED CASES OF MALARIA IN THE FEDERAL CAPITAL TERRITORY, ABUJA

BY

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NIGERIA.

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BEING A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, NASARAWA STATE UNIVERSITY, KEFFI IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF SCIENCE (M.Sc.) DEGREE IN STATISTICS

DEPARTMENT OF STATISTICS,
FACULTY OF NATURAL AND APPLIED SCIENCES, NASARAWA STATE UNIVERSITY-KEFFI,
NIGERIA.

DECEMBER, 2019

DECLARATION

I hereby declare that this dissertation has been written by me and it is a report of my research work. This work has not been presented elsewhere for the award of any academic program in any institution. All quotations are indicated and sources of information specifically acknowledged by means of bibliography.

…… ……

OMALE OMOSHI YOHANNA **Date**
NSU/MSC/STA/0034/17/18

CERTIFICATION

The dissertation "Time series Analysis of reported cases of Malaria in the Federal Capital Territory, Abuja" was carried out by Omale Omoshi Yohanna and meets the regulations governing the award of Master of Science (M.Sc.) Degree in Statistics of the School of Postgraduate Studies, Nasarawa State University, Keffi and is approved for its contribution to knowledge.

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DEDICATION

This dissertation is dedicated to Almighty God who is the Alpha and Omega.

ACKNOWLEDGEMENTS

My profound gratitude goes to the Almighty God, for granting me wisdom, protection and understanding during this course of study.

I wish to appreciate my parents Mr. & Mrs. Omale Ogba Agbazo for their moral and financial support. My thanks also go to my supervisor Dr. (Mrs.) M.U Adehi, who patiently assisted me in motherly manner during Data Analysis.

I must also thank my internal supervisor Dr. M. O. Adenomon for the effort rendered to ensure that Data Analysis was done and well interpreted for real life situation.

My appreciation goes to my very good friends and course mates; your relentless encouragement helped me in making this project a reality and to everyone who contributed in one way or the other, thank you for your love, encouragement and support.

ABSTRACT.

This research work focus on the Trend and seasonality reported cases of Malaria in the Federal Capital Territory, Abuja. Using monthly Data that was obtained from National Bureau of Statistics, (NBS). This study implemented the decomposition model, SARIMA model and Negative binomial regression model for malaria cases among children and adult, and pregnant women. The results revealed that malaria incidence was highest in June and lowest in December for overall malaria incidence; highest in May and lowest in December for malaria cases among pregnant women while malaria cases was highest in June and lowest in November among children and adult. SARIMA $(0, 1, 1) \times (0, 1, 1)_{12}$ was the preferred model to forecast the malaria cases considered in this study. Lastly, the trend analysis of the malaria cases using Negative binomial regression revealed a significant annual decrease in the cases of malaria considered in the Federal Capital Territory, Abuja. This study recommended that more awareness campaign against malaria and adequate distribution of insecticide treated nets should be intensified as there are possibility to eradicate this menace in the Federal Capital Territory, Abuja.

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CHAPTERONE

INTRODUCTION

1.1 Background to the Study

Malaria is one of the world's common and serious infectious diseases which cause at least one million deaths globally every year. The majority of malaria occurred in the developing countries and the proportion keeps increasing annually because of dilapidated health facilities, deteriorating health system, persistent drug and insecticide resistance, climate change experiences, natural disaster, etc. (Cheesbrough, 2005)

Malaria is a mosquito borne disease caused by a parasite called plasmodium (Henderson, 2016). This plasmodium has four species which include plasmodium falciparum, plasmodium vivax, and plasmodium ovale and plasmodium malariae. Malaria parasite is transmitted from one person to another through the bite of a female Anopheles Mosquito which requires blood to nurture her eggs. When Malaria parasites enter the blood stream of a person, they infect the red blood cells and destroy it. The destruction of these essential cells leads to fever and flu-like symptoms such as chills, headache, muscle aches, tiredness, nausea, vomiting, diarrhea and if not treated leads to coma and sometimes death (Thomas, 2014).

The symptom of malaria infection involves sessions of fever that coincide with parasites bursting out of red blood cells, chills, sweating, headache, muscle ache, nausea, vomiting, insomnia, tastelessness, body weakness and so on. The malaria symptoms in the Federal Capital Territory Abuja, consist of severe anemia, fever, and convulsion, abnormal breathing, extreme weakness, hypoglycemia, circulatory collapse, edemas, septicemia, occasional kidney failure, and trauma in children. The one-fifth of patients die of severe malaria infection despite being admitted to the hospitals for treatment (Ezedinachi et al, 2008)

It is discovered that there has been a very little change in the geographical distributions of malicious areas but within the countries, areas of rural economic exploitation have become focus for intense malaria transmission. The malaria situation in some area councils constitutes a leading cause of poverty to the inhabitant of the Federal Capital Territory, Abuja. (Rose, 2017)

The African region has the greatest number of people exposed to stable malaria transmission; the greatest burden of malaria morbidity and mortality in the world. Several factors appear to be responsible for the abundance of the mosquitoes and the result suggested that concerted efforts have been made by stakeholders to reduce the abundance of malaria vectors in the rural areas to prevent an adverse outbreak. (Wenceslaus, 2000).

Mosquito proboscis consists of six different shafts. Four are cutting and piercing tools; a fifth is for transports blood from the host and the sixth one is for transports saliva, though it acts as an anticoagulant for the blood going in the other direction. The saliva also transmits the organisms of Malaria, yellow fever, dengue, and most of the other diseases for which mosquitoes are notorious. When a mosquito punctures “bites” into the flesh, one usually feels an allergic reaction to the saliva, which causes the swelling, itching and also helps explain why some people suffer more than others when their skins are invaded. Some mosquito species are nocturnal, diurnal, or crepuscular. (Philips 2016).

More so, they also differ in their preferences for attitudes. The flight habits of mosquitoes depend on the species and most domestic species remain fairly close to their point of origin. The flight range for females is usually longer than that of males. Many times wind is a factor in the dispersal or migration of mosquitoes. Most mosquitoes stay within a mile or two of their sources. However, some have been recorded as far as 75 miles from their breeding source. The length of life of the adult

mosquito usually depends on several factors: temperature, humidity, sex of the mosquito and time of year. Most males live a very short time, about a week; and females live about a month depending on the above factors. (Smith et al, 2002)

Mosquito goes through four separate and distinct stages of its life cycle and they are: -Egg, Larva, Pupa, and Adult (Sherman, 2017)

Egg: Egg is laid one at a time and they float on the surface of the water but in the case of Culex and Culiseta species, the eggs are stuck together in rafts of a hundred or more. .Anopheles and Aedes species do not make egg rafts but lay their eggs separately. Culex, Culiseta, and Anopheles lay their eggs on the water while Aedes lay their eggs on damp soil that will be flooded by water. Most eggs hatch into larvae within 48 hours. Culex Mosquitoes lay their eggs on the surface of fresh or stagnant water and the water may be in tin cans, barrels, horse troughs, ornamental ponds, swimming pools, puddles, creeks, ditches, or marshy areas. It usually lay their eggs at night and it lay a raft of eggs every third night during its life span/cycle. Anopheles mosquitoes lay their eggs singly on the water, not in rafts while Aedes mosquitoes lay their eggs singly on damp soil. (Bruce-Chwatt, 2017)

Larva: The larva/larvae live in the water and come to the surface to breathe. They shed their skin four times while growing larger and after each molting, the larvae have siphon tubes for breathing and hang from the water surface. *Anopheles* larvae do not have a siphon and they lay parallel to the water surface. It feeds on micro-organisms and organic matter in the water and it takes larva up to four days before changes to a pupa (Sherman, 1998).

Pupa: This stage is a non-feeding stage but a resting time and from this stage that mosquito turns into an adult. It takes about two days before the

adult is fully developed and when development is completed, the pupa skin splits and the mosquito emerges as an adult. (Laveran, 1978)

Adult: The newly emerged adult rests on the surface of the water for a short time to allow itself to dry and all its parts to harden. More so, the wings have to spread out and dry properly before it can fly. The egg, larvae and pupae stages depend on temperature and species characteristics as to how long it takes for development. For instance, Culextarsalis might go through its life cycle in 14 days at 70^{o} F and take only 10 days at 80^{o}F. Some species have naturally adapted to go through their entire life cycle in as little as four days or as long as one month. (Salako, 1991)

According to the Federal Ministry of Health (2015), Malaria is responsible for 60% of in- and out-patient visits to health facilities; 30% of childhood deaths; and 11% of maternal deaths. Furthermore, the Federal Ministry of Health (FMH) estimated a financial loss from malaria (in the form of treatment costs, prevention, loss of man-hours, etc.) to be roughly thirteen (13) million Naira annually. With these staggering statistics, it is clear that health is a prerequisite for economic prosperity. The disease is directly contributing to poverty, low productivity, and reduced school attendance in the Federal Capital Territory, Abuja.

According to National Institute of Allergy and Infectious Diseases (2008), Malaria is caused by a microscopic parasite called plasmodium which comprises of four species and these parasites infecting humans to cause malaria but plasmodium falciparum is the deadly one. Plasmodium is transmitted to people by blood-through mosquitos' bite and is described as malaria "vector" because it spreads but doesn't cause disease. The plasmodium has a complex life cycle involving the infection and destruction of red blood cells and the red blood cells burst, freeing the parasites to attack other red blood cells and from there the symptoms of malaria may begin to surface. Malaria

may also cause by the bites of Anopheles, a dirty environment of stagnant water around the vicinity/compound.

Antimalarial drugs have been seen widespread use over the last century, including Quinine, Chloroquine, Mefloquine, Sulfadoxine-Pyrimethamine, and Amodiaquine. Misuse of these drugs, however, has led to growing resistance from malaria parasites. Over the last decade new Artemisinin-Based Drugs - Artesunate, Artemether, and Dihydroartemisinin - have become available. In an attempt to prevent resistance, these drugs are now used in combinations with drugs from a different class forming Artemisinin Combination Therapies (ACTs) (Peters, 2017).

1.2 Statement of the Problem

The malaria infectious is increasingly becoming a disease of serious concern to everybody and the significant impact of malaria in human existence. The Federal Capital Territory becomes more ravaging and damaging as a result of high morbidity and mortality experienced in different parts of the Federation. However, the stagnant water (breeding grounds for the Anopheles mosquito) led to the research of this study; whether the inability of Government and stakeholders in the Federal Ministry of Health sector to device appropriate workable measures in the areas of technology.

The rate of malaria incidence in the Federal Capital Territory, associated with stagnant water led to the research whether malaria in pregnancy women, malaria in children and adult in the case study is increasing or decreasing.

1.3 Aim and Objectives of the Study

Aim: The aim of this study is to carry out a Time Series Analysis of reported cases of malaria infectious in the Federal Capital Territory, Abuja

Objectives: The specific objectives of this study are to: -

a) Investigate the seasonality of reported cases of malaria among, pregnant women, children and adult in the Federal Capital Territory, Abuja.

b) Fit a time series model to the reported cases in the Federal Capital Territory, Abuja.

c) Predict the future occurrence of malaria cases reference to the SARIMA Model.

d) Investigate the trend in the reported cases of Malaria prevalence in the Federal Capital Territory, Abuja.

1.4 Significance of the Study.

The significances of this study will help to: -

a) Aid the officeholders to have a focus on how to prevent a malaria prevalence in the Federal Capital Territory, Abuja.

b) Create awareness to the inhabitants of rural areas and the Federal Capital Territory on the consequences of malaria-endemic,

c) Make Government takes adequate measures towards eradication of malaria from the study area,

d) Serves as a great significance to different fields of studies dealing with malaria cases and to forecast how mosquitoes can be eradicated in the Federal Capital Territory Abuja.

1.5 Scope of the Study

The scope of this research work covers the use of time series analysis on the trend and seasonality of reported cases of malaria prevalence in the Federal Capital Territory, Abuja. And the data used for this research work is extracted from the National Bureau of Statistics (NBS) from January 2009 to December 2018.

The research also concerns with the number of in- and out-patients admitted on malaria cases using time series analysis. Although, for the accuracy and reliability of data, the researcher used National Bureau of Statistics data; since it has a

comprehensive data on malaria cases for all the six (6) Area Councils in the Federal Capital Territory, Abuja.

1.6 Definition of Operational Terms and Acronyms

Time Series: - Time Series is a record of observations measuring the certain quantity of interest at regular or irregular intervals of time and the observations may be recorded daily, weekly, quarterly, yearly, or bi-annually (Adenomon, 2016).

Analysis-Analysis is the process of breaking a complex topic or substance into smaller parts to gain a better understanding of it.

Trend-This is the long-term movement in a series in the same direction over a long time. It is usually characterized as a continuous increase or decrease in the values on a variable over time

Seasonality-Seasonality is a characteristic of a time series in which the data experiences regular and predictable changes that recur every calendar year. This also refers to identical or almost identical patterns, which a time series appears to follow during corresponding months of successive years due to the mainly recurring event that takes place annually.

Malaria – Malaria is a mosquito-borne disease caused by a parasite. People with malaria often experience fever, chills, and flu-like illness.

Infection: -Infection is the invasion of an organism's body tissues by disease-causing agents, their multiplication, and the reaction of host tissues to the infectious agents and the toxins they produce. Infectious disease, also known as transmissible disease or communicable disease is illness resulting from an infection.

Federal Capital Territory: Nigeria's Federal Capital Territory is located in central Nigeria. Abuja, the Capital City of Nigeria is situated in this

Territory. FCT was found in 1976 from part of Nasarawa, Niger, Kaduna and Kogi State. It is within the middle belt region of the country. It is administered by the Federal Capital Territory Administration, headed by a Minister appointed by the President of the Federal Republic of Nigeria.

Forecasting: - Is the process of making predictions of the future based on past and present data and most commonly by analysis of trends

Mean Absolute Deviation (MAD): - The Mean Absolute Deviation expresses accuracy in the same units as the data, which helps conceptualize the amount of error. Outliers have less of an effect on MAD than on MSD.

Mean Absolute Percentage Error (MAPE): - Mean Absolute Percentage Error expresses accuracy as a percentage of the error, the number is a percentage, it can be easier to understand than the other statistics.

Mean Squared Deviation (MSD): - A commonly- used measure of accuracy of fitted value time series values. Outliers have a greater effect on MSD than on MAD.

WHO: - World Health Organisation

SARIMA: - Seasonal Autoregressive Integrated Moving Average

ACF: - Autocorrelation Function

PACF: - Partial Autocorrelation Function

SAR: - Seasonal Autoregressive

SMA: - Seasonal Moving Average

AIC: - Akaike Information Criterion

BIC: - Bayesian Information Criterion

MCA: - Malaria in Children and Adult

MI: - Malaria Infectious

LL: - Log-Likelihood

LLIN: - Long-Lasting Insecticidal Net

ANC: - Antenatal Care

IPTP: - Intermittent Preventive Treatment in Pregnancy

IRS: - Indoor Residual Spraying

ITMN: -Insecticide-Treated Mosquito Net

SMC: - Seasonal Malaria Chemoprevention

UHC: - Universal Health Coverage

FMH: - Federal Ministry of Health

ACTs: - Artemisinin-based Combination Therapies

CHAPTER TWO

LITERATURE REVIEW

2.1 Conceptual Framework

2.1.1. Concept of Malaria infection

Globally, Malaria is increasingly becoming a disease of serious concern to everybody because day by day, the impact of Malaria in human existence, all over the world, becomes more ravaging and damaging as a result of high morbidity and mortality experienced in different parts of the globe especially the developing countries like Nigeria. Malaria parasite has been in existence since the dawn of time. Hippocrates, a physician born in ancient Greece, today regarded as the "father of medicine" was the first to describe the manifestation of the disease. Its association with stagnant water (breeding grounds for the Anopheles Mosquito) led the Romans to begin drainage program, the first intervention against Malaria. The first recorded treatment of Malaria dates back to 1600, when the bitter bark of Cinchona tree in Peru was used by the native Indians. (Sherman, 1998).

Not until 1889 was the protozoa (single celled parasite) that causes Malaria discovered by Alphonse Laveran and only in 1987 was the Anopheles Mosquito demonstrated to be the vector for the disease by Ronald Ross. The discovery of Ronald Ross was followed by a series of important works which not only enlarged the understanding of Malaria but also supplied useful knowledge in the combat against Malaria and prevention of Malaria. Despite initial success, there was a complete failure to eradicate Malaria in many countries (Mills et al; 2018).

The world's population- are at risk of Malaria and one million people die each year as a result of malaria infection. In Nigeria, 25% of Malaria death cases occur in Federal Capital Territory, Abuja.; particularly, 1 in 5 childhood deaths are caused by

Malaria; while 1, 000 pregnant women and 800 infants die of Malaria annually. (Ofovwe and Erejie, 2010).

Malaria accounts for an estimated 2 to 3 million deaths annually and is also responsible for untold morbidity in approximately 300 to 500 million people annually. Susceptible groups are children and adults who never acquired immunity. (WHO, 2017).

Malaria is said to kill about one African (whether child or adult) every 15 secs and roughly 300, 000 Nigerian children annually (Salako, 2002). Malaria is responsible for over 10% of the overall African disease burden. Children under five years of age (22% of the population) and pregnant women (20% of the population) are the most vulnerable to Malaria disease (Guillet et al, 2018).

Nigeria is known for a high prevalence of malaria and it is a leading cause of morbidity and mortality in the country (Onwujekwe et al, 2000). Available records show that at least 50% of the population of Nigeria suffers from at least one episode of Malaria each year and Malaria accounts for over 45% of all out-patient visits (Ejezie et al, 1991). It was reported that malaria prevalence in 2000 was about 2.4 million times responsible for an estimated average annual reduction of 1.3% in economic growth for the countries with the highest burden, Nigeria inclusive, (Federal Ministry of Health, 2017).

It imposes a great burden on the country in terms of pains and trauma suffered by its victims as well as loss in output and cost of treatments (Onwujekwe et al, 2010).

2.2 Review of Previous Studies

Many researchers have been done in the past regarding incidence and mortality in Malaria reported cases. The need to review some of these previous works and other related topics is necessary as it will add value to this study.

Durueke (2011) carried out a research on the incidence, management and bionomic of malaria in children under 5 years of age in parts of Isiala Mbano L.G.A, Imo State, from January 2004 to December 2005. Using a seasonal ARIMA Model for forecasting, the result revealed that the incidence of malaria in the studied area was inversely proportional to the socio-economic levels of the areas under study. The research revealed that there was an increased incidence of malaria reported cases when socioeconomic and standard of living decreased.

Gerritsen et al (2013) carried out an analysis on malaria incidence in Limpopo Province South Africa from 2016 to 2018, using chi-square test of independence and time series analysis. The result showed that out of 58768 cases of malaria reported including 628 deaths, the mean incidence of malaria was 124.5 per 1, 000 per person and the mean mortality rate was 1.1% per season. Also, there was a decreasing trend in the incidence over time, and the mean incidence in males was higher than in females. Finally, the result revealed that incidence in malaria peaked at the age of 35 to 39 years, decreased with age from 40 years and is lowest in 0 – 4 years old.

Ayeni (2018) conducted a research on "Malaria Morbidity in Akure South West, Nigeria: By applying the method of time series analysis, the result revealed that malaria morbidity was generally low before 2009 and that the reported cases of malaria increased from 43, 533 in 2009 to about 62, 121 case in 2018. From the result also, malaria morbidity index revealed an increase of 0.005 annually between 2010 and 2018.

Yeshiwodim, et al (2009) carried out a research on Spartial analysis of malaria incidence at the village level in areas with unstable transmission in Ethiopia from January, 2002 to December, 2006. using the method of Poisson Regressions analysis, the result indicated the presence of significant spartio-temporal variation and a decrease in the incidence of malaria with increasing age. Yeshiwodim, et al

concluded that the incidence of malaria varies according to gender and age, with males age 5 and above showing a statistically higher incidence.

Korenromp et al (2007) also carried out a singular study. The result revealed that the exploration of the incidence of malaria, precipitation, temperature and vegetation for 1997 to 2003 showed no clear trend, and suggests a seasonal dependency in the series with a 6-month period for the incidence and a 12-month period for rainfall, temperature and vegetation.

Nwankwo and Okafor (2009) carried out a research on the effectiveness of insecticide treated bed nets (ITNs) in malaria prevention among children aged 6 months to 5 years in Umungwa Obowo L.G.A, Imo State of Nigeria between June and September 2006. From the 100 children selected and randomly assigned either treated bed nets or traditional bed nets, and using a chi-square test of independence, the result revealed that there was a significant difference in the malaria morbidity situation among the two groups. That is to say, morbidity due to malaria was higher in children that used traditional bed nets than the other group.

Opara (2001) carried out a study on "The effects of malaria during pregnancy on infant mortality in Abia State Nigeria between 1993 and 1999". Using chi-square test for independence, the result showed that malaria during pregnancy increased neonatal mortality by lowering birth weight.

Adebola and Okereke (2007) conducted a study "Increasing Burden of Childhood Severe Malaria in a Nigerian Tertiary Hospital: Implication for control, between January 2000 and December 2005". Using logistic Regression, the result revealed that severe Malaria constituted an important cause of hospital admission among Nigerian children especially those aged below 5years. The result also revealed that there was significant increase in the proportion of cases of severe malaria from 2000 to 2005.

Greenwood et al (2013) carried out a research on the evolution of malaria mortality and morbidity after the emergence of chloroquine resistance in rural area of the Gambia, West Africa between 1992 and 2004. Applying the method of univariate logistic regression and time series analysis, the result revealed that mortality attributable to malaria did not continue to increase dramatically, in spite of the growing resistance to chloroquine as first-line treatment, until 2003. The result also showed that malaria morbidity and mortality followed parallel trends and rather fluctuated accordingly to rainfall.

Baird, et al (2002) conducted a research on the seasonal malaria attack rates in infants and young children in northern Ghana from 1996 to 1997. Using fisher's exact test and chi-square test of independence, the result showed that the mean parasitemia count at the time of reinfection in the dry season roughly equaled that in the wet season. Having reviewed some of these related literatures, we shall now in this paper examine the modeling and forecasting malaria reported cases using SARIMA models.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Sources of Data

The data used for this research was collected from the National Bureau of statistics Head Quarter Abuja, Nigeria. In the course of this study, the researcher resorted to working with secondary data because such data were already documented for research consumption and other purposes. The researcher used secondary data because the data are readily available; hence, it saves time and resources. (National Bureau of Statistics, 2018)

3.2 Population of the Study

The population targeted for the study was all reported cases of malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018.

3.3 Study Sample

The researcher sampled only reported cases and prevalence of Malaria recorded in the Federal Capital Territory, Abuja from 2009 to 2018.

3.4 Methods of Data Collection

For this study, the researcher consulted documented data that was collected recorded and documented by the National Bureau of Statistics (NBS) on the cases of Malaria prevalence in the Federal Capital Territory Abuja.

3.5 Technique for Data Analysis

Base on the objectives of the study, the techniques adopted for this analysis are;

i. Time Series analysis

ii. SARIMA Model and

iii. Negative Binomial Regression Model

3.5.1 Time Series Analysis (T.S.A)

Shittu and Yaya (2016) defined Time Series as a set of values taken by a variable over time (such as daily sales, weekly order, monthly overheads, yearly income, etc.) and plotted as chronologically ordered numbers or data points to yield valid statistical inference; such values must be repeatedly measured, often over four to five years. Time series consist of four components namely: -

i. Trend or Secular Movement
ii. Seasonal Variation
iii. Cyclical Variation and
iv. Random or Irregular Variation

Trend: Trend is denoted by (T_t) and it is referring to the general direction in which the time plot appears to be moving. In other words, a time series is said to contain a trend if the mean of the series changes systematically with time. This systematic change may be linear, quadratic or exponential. If there is no trend, it is called a stationary series.

Seasonal Variation: This seasonal variation is denoted by (S_t) and it is referred to identical patterns which the time series follow during corresponding months or quarters of success. For instance, an event likes Sallah, Christmas, Easter, marriages, and so on.

Cyclical Variation: The cyclical variation is denoted by (C_t) and it is referred to as the long-term oscillation about the trend line. The oscillations are not exactly to another. For example, the business cycle represents intervals of prosperity, recession, depression, and recovery.

Irregular Variation: The irregular variation is denoted by (I_t) and it is referred to as sporadic motions of a time series due to the change of an event such as war, flood, earthquake, strike, fire outbreak, etc.

3.5.2 Time Series Model

Multiplication Model: This is the method of adjusting the corresponding quarter by a constant percentage.

The method is given as $Y_t = T_t X S_t X C_t X I_t$ (1)

Additive Model: It assumes that there is a constant and absolute difference of the actual data and the model is given as; $Y_t = T_t + S_t + C_t + I_t$ (2)

Where

Y_t= Actual value of the variable of interest

T_t = Secular trend

S_t = Seasonal Component

C_t= Cyclical Component and

I_t = Irregular Component

3.5.3 The objective of Time Series Analysis

The modest objective of any time series is to provide a concise description of historical series. This may consist of a few summary statistics and also a graphic representation of data. The more ambitious task is to forecast future values of a series. Also, the objective of the time series includes description, explanation, prediction, and control.

3.5.4 Estimation of Trend Effect

Trend effect can be estimated in several ways these include:

i. The freehand method

ii. The method of semi average

iii. The method of moving average and

iv. The least-squares method.

The Freehand Method: This method consists of fitting a trend line by looking at the graph. The freehand method is the simplest method of finding a trend line; the procedure involves first the plotting of the time series on a graph and fitting a straight line through the plotted points in such a way that the straight line shows the trends of the series. At an earlier time, we estimate through individual judgment.

The Method of Semi Average: This method consists of separating the data into the part and averaging the data in each part thereby obtaining two points. The average of each part is calculated and then a trend line through these averages is filled. This method is simple but does not give a good result.

Method of Moving Average: This is a series of successive average secured from a given data and the technique of using moving average is to replace a particular measurement by the arithmetic mean of series to the Centre. When an odd number of measurements is chosen, the moving average is centered between two (2) observed measurements. The problem with this method is that the data at the beginning and the end of the series are lost. It is also creating cycles that were not present in the original data.

For example, given a set of data $X_1, X_2, \cdots X_N$, the moving average of the order N will be: $\frac{X_1 + X_2 + \ldots + X_n}{N}$ (3)

The second trend value is:

$$\frac{X_2 + X_3 + \ldots + X_n + 1}{N} \quad (4)$$

And the third trend value is:

$$\frac{X_3 + X_4 + \ldots + X_n + 1}{N} \quad (5)$$

Advantages of Moving Average

1. It reduces the amount of variation present in a set of data
2. Estimation of trend can be achieved in several possible ways
3. Any unit of time can be used such as weekly, monthly, quarterly, yearly, etc.

3.5.6 Method of Least Squares

Adenomon (2016) this method is one of the best methods of obtaining trend values in the form of a straight line called the line of best fit. The line is given by

$$y_t = \alpha + \beta t + \varepsilon \quad (6)$$

Where

y_t =The time series value

α =The intercept

β = The slope and

ε = The error term

The formulas are given below:

$$\beta = \frac{\mathbf{n}\sum \mathbf{y} - \sum \mathbf{y}\sum \mathbf{t}}{\mathbf{n}\sum \mathbf{t^2} - (\sum \mathbf{t})^{\mathbf{2}}} \quad (7)$$

$$\alpha = \frac{\sum Y}{N} - \beta\frac{\sum t}{N} \qquad \text{Or } \bar{\mathbf{y}} - \beta_t^- \quad (8)$$

Where n is the number of observation and "t" is coded from 1 to n

3.6.0 SARIMA Models

SARIMA model combines non-seasonal and seasonal components, and can be specified as SARIMA (p,d,q) × (P,D,Q), where p, d, and q refer to the orders of the non-seasonal autoregressive (AR), non-seasonal differencing and non-seasonal moving average (MA) parts of the model. P, D, and Q

refer to the orders of the seasonal AR, seasonal differencing and seasonal MA parts of the model. The AR process accounts for previously observed values up to a specified maximum lag, plus an error term. The process of difference is referred to as the integral part that accounts for the stabilization of the data by removing seasonality or trend, while the MA process accounts for previous error terms, making forecasting easier. (Shitu and Yaya, 2016)

SARIMA is a Box-Jenkins technique that takes into account of time series data and decomposes it to: -

AR (Autoregressive) process- a real-valued stochastic process (Y_t) is said to be an AR process of order p, denoted by AR (p) if

$$Y_t = a_t y_{t-1} + a_2 y_{t-2} + \cdots + a_{1p} y_{t-p} + \varepsilon_t \quad (9)$$

The value of the AR (p) process at time (t) is therefore regressed on its past p values plus a random shock.

MA (Moving Average) process – a real-valued stochastic process (Y_t) is said to be an MA process of order q, denoted by MA (q) if there exists $b_t, \cdots, b_q$ and a white noise (ε_t) such that

$$y_t = b_o \varepsilon_t + b_1 \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q} \quad (10)$$

The value of MA (q) process at time t is therefore regressed on its past errors.

ARMA- Moving Average MA (q) and Autoregressive AR(p) processes are special cases of so-called autoregressive moving average processes (ARMA), a real-valued stochastic process (Y_t) is said to be an ARMA process of order (p, q), denoted by

ARMA (p, q) if it satisfies the equation given by:-

$$Y_t = \varepsilon_t + \left(a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p}\right) + \left(b_o \varepsilon_t + b_1 \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q}\right) \quad (11)$$

This can be re-written as: - $\emptyset(B) y_t = \theta(B)\varepsilon_t$, where $\emptyset(B) = 1 + a_1 B + \cdots + a_p B^p$ and $\theta(B) = 1 + b_1 B + \cdots + b_q B^q$ are the characteristic polynomials of the AR part and the MA part of an ARMA (p, q) Process(Y_t), B is the back-shift (lag) operator.

ARIMA Process: - The Autoregressive Integrated Moving average (ARIMA) model, is a broadening of the class of ARMA models to include differencing. A process (Y_t) is said to be an ARIMA (p, d, q) if $(1 - B)^d (Y_t)$ is a causal ARMA (p, q).

The corresponding ARIMA equation is $\emptyset(B)(1 - B)^d X_t = \theta q(B)\varepsilon_t$ (12)

SARIMA Process: - For a non-stationary time series possibly containing seasonality, that is, the seasonal periodic component repeats itself after every s observation. Box and Jenkins (1976) defined a general multiplicative seasonal ARIMA model (SARIMA) as:

$$\emptyset_p(B)\varphi_p(B^S)(1 - B)^d (1 - B^S)^D y_t = \theta_q(B)\theta_Q(B^S)\varepsilon_t \quad (13)$$

Where$\emptyset_p(B), \varphi_p(B^S), \theta_q(B)$, and $\theta_Q(B^S)$are characteristic polynomials of order p, P, q and Q respectively, d and D are the orders of non-seasonal and seasonal differencing respectively.

Box and Jenkins (1976) bases the model selection on four stages, that is, the first stage is by identification, the second stage is by estimation of coefficients, the third stage is by diagnostic checking and the fourth stage is by forecasting.

1. (First Stage) Model Identification

The objective of this step is to determine the possible SARIMA model that best fit the time series data under consideration. SARIMA model is appropriate for stationary time series, therefore; stationarity condition must be satisfied Augmented Dickey-Fuller (ADF) Test to see whether the seasonal differenced series is stationary. The values of p, q, P and Q are then determined at this step by looking at the patterns of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). (Dickey et al, 1979)

2. (Second Stage) Estimation of Coefficients

The parameters are estimated by the maximum likelihood estimation method. (Akaike, 1976).

In this study, the model with the minimum value of AIC is the judge as to the best model and it is given by $\mathrm{AIC} = -2\ln(\mathrm{L}) + 2\mathrm{K}(6)$ (14)

where k = P + q + 1 and L = the maximum likelihood value

3. (Third Stage) Diagnostic Checking

This step involves checking whether the residuals follow a white noise process and ensure that the estimated parameters are statistically significant. It is done by inspecting the: -

a) Autocorrelation Function (ACF) plots of the residuals,

b) Probability plots of the residuals

c) Residuals Q-Q plots

d) (JB- Test) Jarque Bera test can also be used to verify normality among the residuals, and if the model fails these diagnostic checks then return to the first stage (Identification Stage) to find a better model otherwise SARIMA model in step two (2) is appropriate. (Dickey and Fuller, 1981)

4. (Fourth Stage) Forecasting Method

The selected SARIMA model in step three (3) was used to forecast malaria reported cases from January 2009 to December 2018. The reported malaria cases for 2018 were used to validate the forecast.

The mathematical expression of the SARIMA model is given as:

$$\varphi(B^S)\emptyset(B)\Delta^d\Delta_S^D X_t = \theta_0 + \theta(B^S)\,\theta(B)\alpha_t \quad (15)$$

The non-seasonal factors are given as:

$$\text{AR: } \varphi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p \quad (16)$$

$$\text{MA: } \theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q \quad (17)$$

The seasonal factors are given as:

$$\text{Seasonal AR: } \varphi(B^S) = 1 - \varphi_1 B^S - \cdots - \varphi_P B^{PS} \quad (18)$$

$$\text{Seasonal MA: } \theta(B^S) = 1 + \theta_1 B^S + \cdots + \theta_Q B^{QS} \quad (19)$$

Where X_t = data series α_t= random error or (with mean zero and varianceδ^2),

B = backward shift operator,$\emptyset$= Coefficient of non-seasonal autoregressive,θ = coefficient of the seasonal moving average Δ^d= difference operator, with d orderof differencing, and Δ_S^D= Seasonal difference operator, with D seasonal order of differencing and s length of the seasonal period.

The major reason for this study is to unfold the current pattern or trend and seasonality of malaria reported cases in the Federal Capital Territory, and to come out with an adequate model for forecasting future trend of malaria. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used to build a predictive tool for malaria surveillance. The order of seasonal model represented by SARIMA (p, d, q) x (P, D, Q) describes Seasonal Autoregressive (SAR) over a maximum order of p years,

differencing order of d adjacent years and moving averages process order of q years.

The Box and Jenkins (1994) approach was used to determine the patterns best describing the malaria time series. Malaria reported cases time plot was also made to detect and fix the problem of non-stationarity. having achieve stationarity, models of varying orders were fitted and compared using normalized Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) 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 coefficients in different time lags were used to determine the parameters of the SARIMA model. The correlation values fell within the confidence limit which was set for the ACF and PACF. (Dickey et al, 1981)

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Data Presentation

Table 4.1.: Overall Monthly Reported Cases of Malaria prevalence in the Federal Capital Territory, from 2009 to 2018

Month	**Yearly Statistics**										
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	TOTAL
Jan.	1481	2001	2405	1912	2212	4118	1801	1224	2009	1010	20173
Feb.	1332	2321	2119	1889	3009	4422	1283	1702	1887	1914	21878
Mar.	2476	1775	1221	1173	2074	4209	1316	897	2102	1196	18439
April	1984	2331	1417	2141	3018	4427	1781	2041	2017	1989	23146
May	1819	2019	2191	2215	3919	4641	2018	2057	1990	2070	24939
June	2411	2512	2918	2483	3046	5032	1189	3103	2018	2024	26736
July	1745	2045	1199	2127	3014	4883	1799	1203	1782	1874	21671
Aug.	2143	2491	2541	1971	3517	5074	1546	2131	1767	1891	25072
Sept.	1671	1983	2512	2019	2818	4784	1415	1304	1196	1213	20915
Oct.	1179	1436	1689	1811	2982	3799	1473	798	1804	1610	18581
Nov.	899	1371	1311	924	2775	3877	1232	809	1614	1067	15879
Dec.	1017	1062	1924	818	2652	3967	1351	625	789	1639	15844
TOTAL	**20157**	**23347**	**23447**	**21483**	**35036**	**53233**	**18204**	**17894**	**20975**	**19497**	**253273**

Source: National Bureau of Statistics, from 2009-2018

Table 4.2: Monthly Reported Cases of Malaria Infectious in Pregnant women (MIP) in the Federal Capital

Territory, from 2009 to 2018

Month	Yearly Statistics										
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**TOTAL**
Jan.	0	0	162	212	519	631	437	479	513	389	3342
Feb.	0	0	183	241	558	607	427	429	417	498	3360
Mar.	0	0	188	231	411	713	378	504	527	529	3481
April	0	0	183	301	495	678	413	519	571	680	3840
May	0	0	149	322	442	810	591	481	563	532	3890
June	0	0	182	258	584	771	424	533	432	589	3773
July	0	0	181	252	670	699	348	523	419	594	3686
Aug.	0	0	158	309	480	808	435	518	513	413	3634
Sept.	0	0	169	315	419	781	514	610	493	516	3817
Oct.	0	0	173	303	577	675	521	337	473	426	3485
Nov.	0	0	189	321	479	788	517	225	244	349	3112
Dec.	0	0	197	210	438	791	489	221	263	318	2927
Total	**0**	**0**	**2114**	**3275**	**6072**	**8752**	**5494**	**5379**	**5428**	**5933**	**42447**

Source: National Bureau of Statistics, from 2009-2018

Table4.3: Monthly Reported Cases of Malaria prevalence in Children and Adults (MCA) in the Federal Capital Territory from 2009 to 2018

Month	**Yearly Statistics**										
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	**TOTAL**
JAN	1079	1311	1897	1752	2112	2789	971	687	1213	891	14702
FEB	1358	1480	1948	1456	1997	2878	1109	987	1133	978	15324
MAR	1687	2799	1797	1672	2139	3018	1301	1220	2211	889	18733
APRI	2011	1882	1973	1984	2317	3782	1211	1401	1313	977	18851
MAY	1987	1761	1697	1078	2457	4017	1513	1076	1144	993	17723
JUNE	1990	1870	1796	1995	2498	4406	1205	1309	2110	1209	20388
JULY	1486	2506	1947	2001	2271	3398	1072	1507	2101	1170	19459
AUG	2001	2987	1828	1331	2378	4219	1006	990	1093	1231	19064
SEPT	1303	1498	1943	1602	2619	5013	1101	1030	824	1711	18644
OCT	1481	1678	1269	997	2708	4217	907	1110	913	994	16274
NOV	1810	1789	1292	1029	2890	4109	678	788	732	1423	16540
DEC	1964	1786	1946	1311	2578	2635	636	410	760	1098	15124
TOTAL	**20157**	**23347**	**21333**	**18208**	**28964**	**44481**	**12710**	**12515**	**15547**	**13564**	**210826**

Source: National Bureau of Statistics, from 2009-2018

4.2 Data Analysis and Results

Time Series Decomposition of overall malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

Table 4.1.1: The Time Series Decomposition for lnOM (InOM = ln of Overall Malaria Prevalence) using Multiplicative Model

Data	Length	No. of Missing value
LnOM	120	0

Fitted Trend Equation of overall Malaria prevalence in the Federal Capital Territory, Abuja is given as

$Y_t = 7.62582 - 0.00112517*t$

The above trend equation shows a monthly decrease of 0.11% in the overall malaria prevalence in the

Federal Capital Territory, Abuja for the period of January 2009 to December 2018

Table 4.1.2 Seasonal Indices of overall Malaria prevalence in the Federal Capital Territory, Abuja

Period(Month)	Index	Percentage (%) index	Remarks
January	1.00517	100.517	Increase by 0.517
February	1.01936	101.936	Increase by 1.936
March	1.02834	102.834	Increase by 2.834
April	1.03081	103.081	Increase by 3.081
May	1.02513	102.513	Increase by 2.513
June	1.03571	103.571	Increase by 3.571
July	1.00755	100.755	Increase by 0.755
August	0.99689	99.689	Decrease by 0.311
September	0.97962	97.962	Decrease by 2.038
October	0.98847	98.847	Decrease by 1.153
November	0.95901	95.901	Decrease by 4.099
December	0.92392	92.392	Decrease by 7.608

Summary:

From table 4.1.2 above, the month of January to July experienced an increased prevalence of malaria with highest prevalence in the month of June with (3.6%) while in the month of August to December experienced decrease prevalence in malaria with lowest prevalence in the month of December (7.6%). This is further amplified by Figures 4.1.1, 4.1.2 and 4.1.3 respectively

Table 4.1.3: Accuracy Measures for malaria prevalence in the overall reported cases in the Federal Capital Territory, Abuja from 2009 to 2018.

Accuracy	MAPE	MAD	MSD
Measures	3.99439	0.30385	0.16201

Table 4.1.4 Forecasts of the overall malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

Period	Forecast	Exponential of the forecast
January	7.52839	1861
February	7.63356	2067
March	7.69965	2208
April	7.71694	2247
May	7.67330	2151
June	7.75127	2325
July	7.53945	1881
August	7.45856	1735
September	7.32822	1523
October	7.39334	1626
November	7.17191	1303
December	6.90843	1001

The forecast in the table 4.1.4 above, revealed a decline in the overall malaria prevalence in the Federal Capital Territory, Abuja for the year 2019

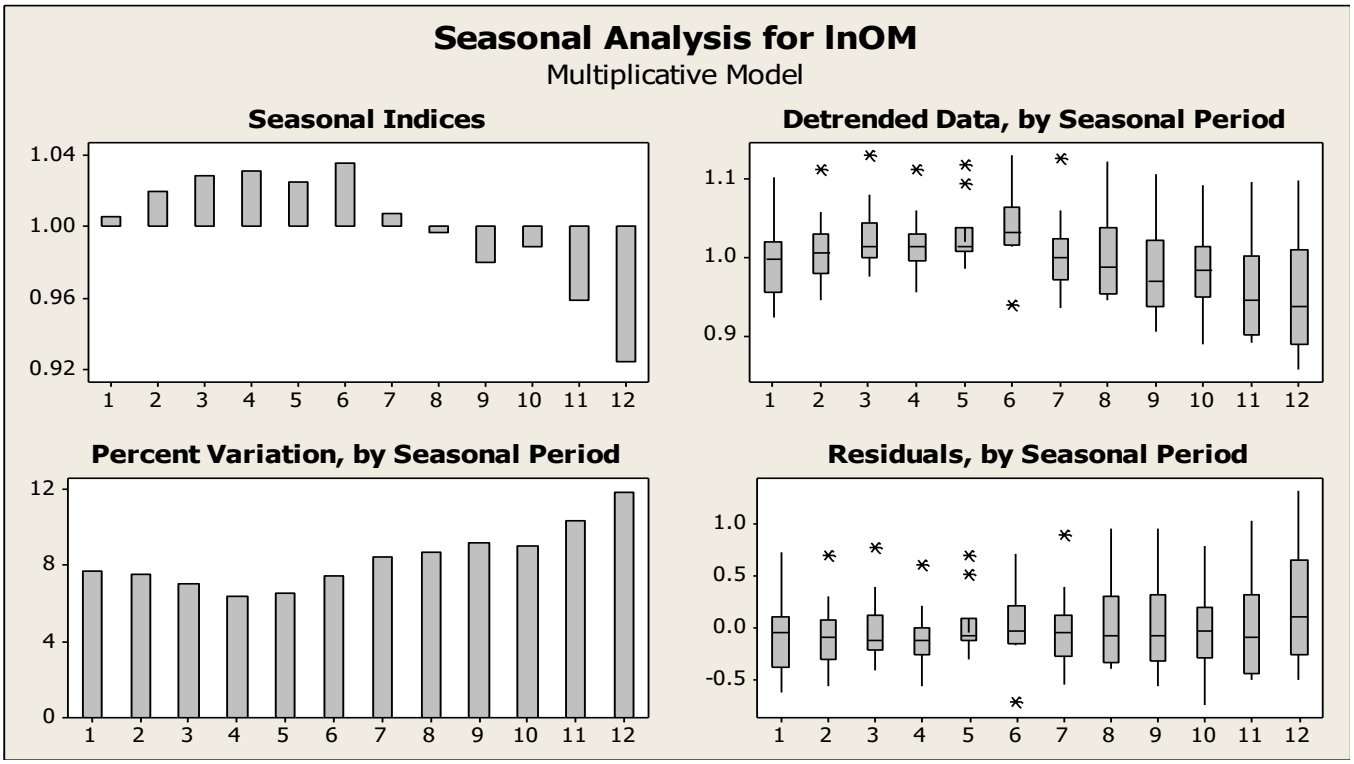

Figure 4.1.1 The Seasonal Analysis of Overall Malaria prevalence in the Federal Capital Territory, Abuja, from 2009 to 2019

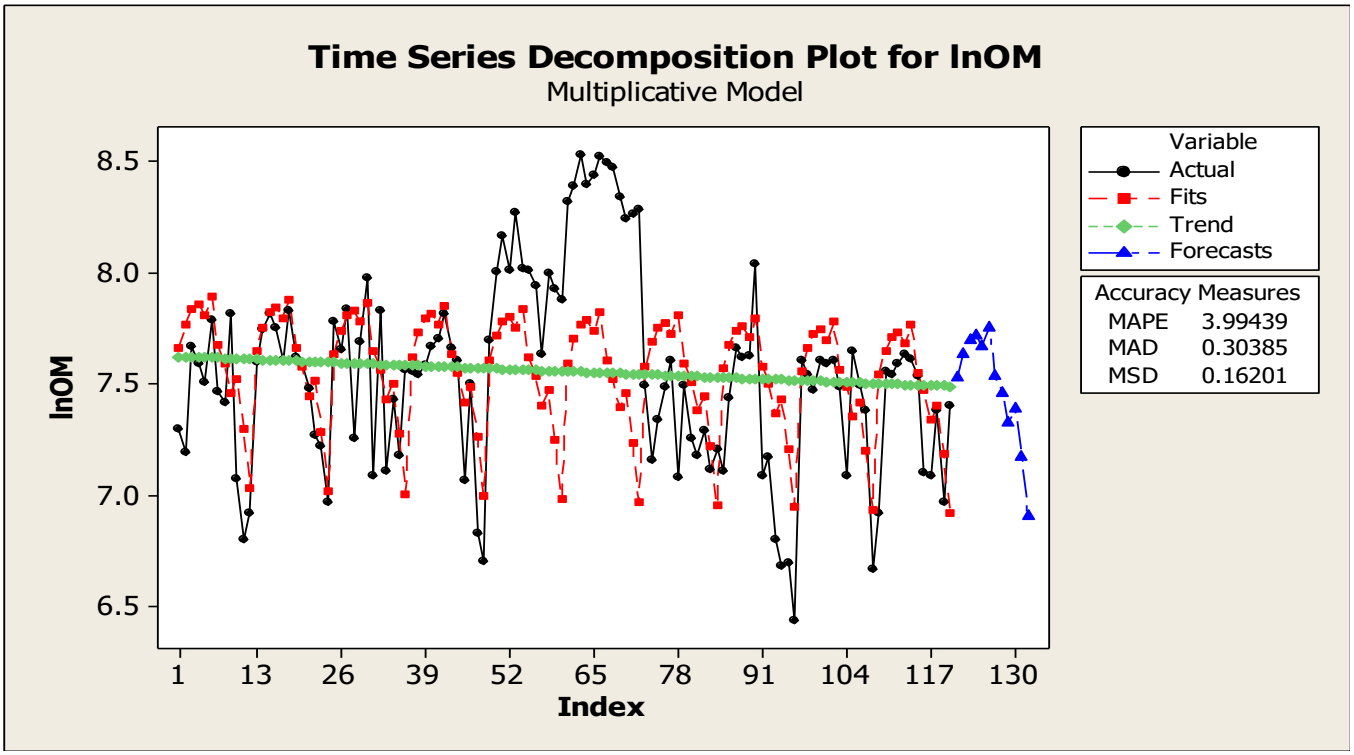

Figure 4.1.2 Summary of Time Series Decomposition of overall Malaria prevalence in the FCT, Abuja from 2009 to 2018.The graph shown the fluctuation of malaria

prevalence, although the prevalence appeared highest in the month of June and the lowest was in the month of December.

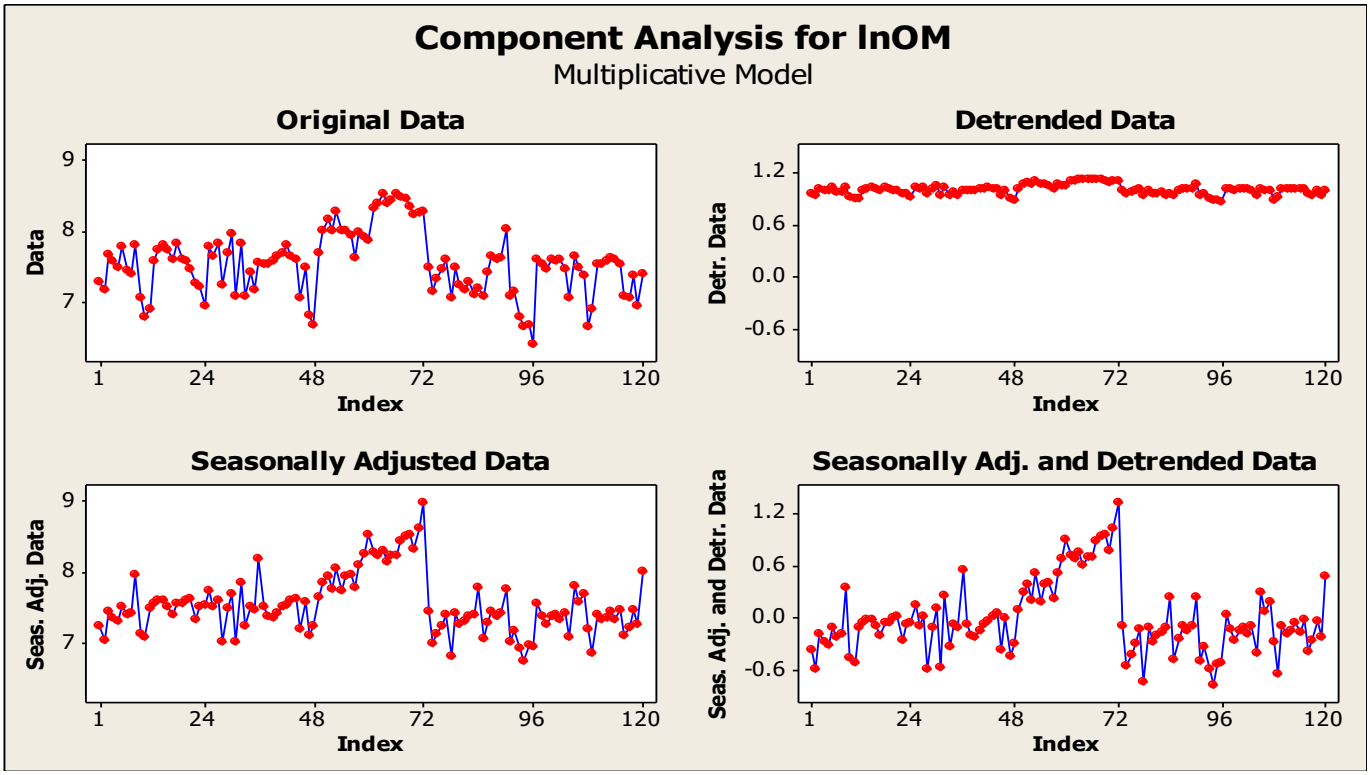

Figure 4.1.3T he Component Analysis of overall Malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018.

Table 4.1.5: Possible SARIMA models for overall Malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

SARIMA	MSE	REMARKS
$(1,1,1)\ X\ (1,1,1)_{12}$	0.0998	AR not significant MA significant and adequate
$(0,1,1)\ X\ (0,1,1)_{12}$	0.1005	MA significant and adequate

The SARIMA $(0, 1, 1)\ X\ (0, 1, 1)_{12}$ was selected as the preferred model because it has the least number of parameters which are significant in the model and also the model is adequate. Which evidence can be seen in the ACF (Autocorrelation

Function) and PACF (Partial Autocorrelation Function) in the Figures 4.1.4 and 4.1.5

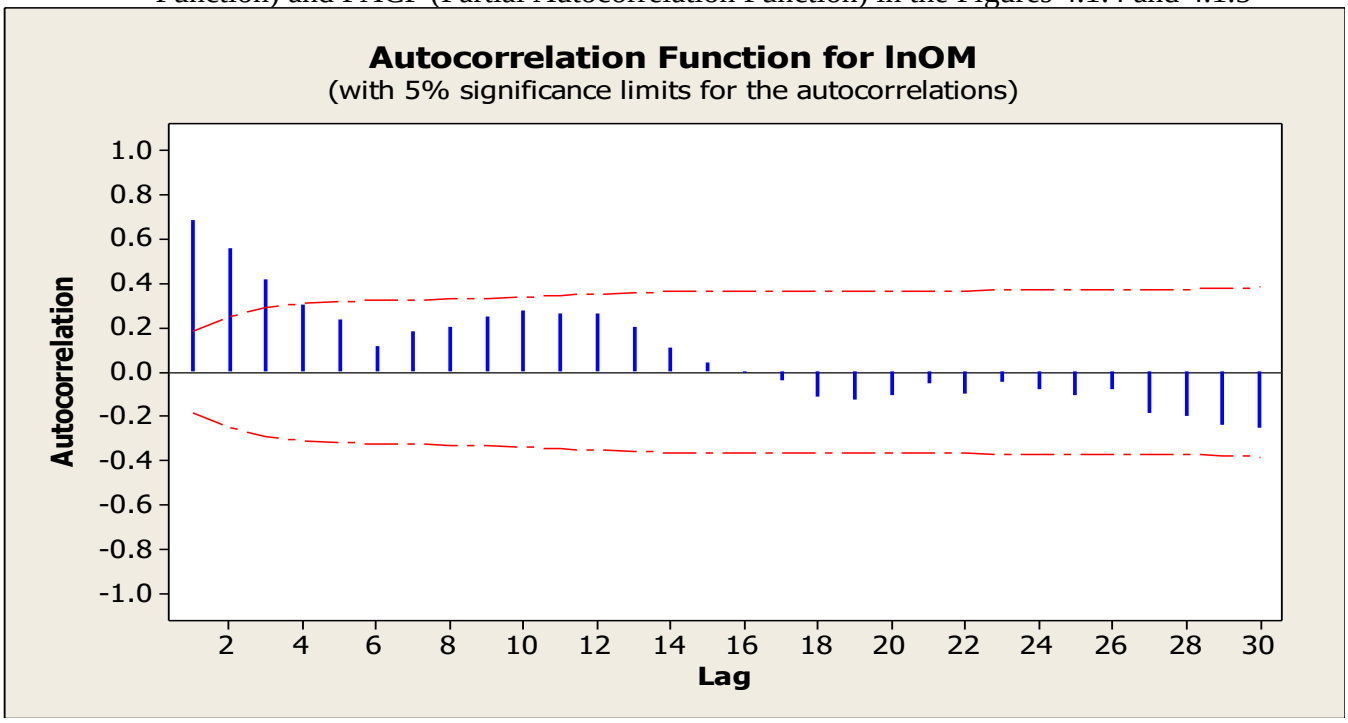

Figure 4.1.4: - SARIMA MODELS using (ACF = Autocorrelation Function for Overall Malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

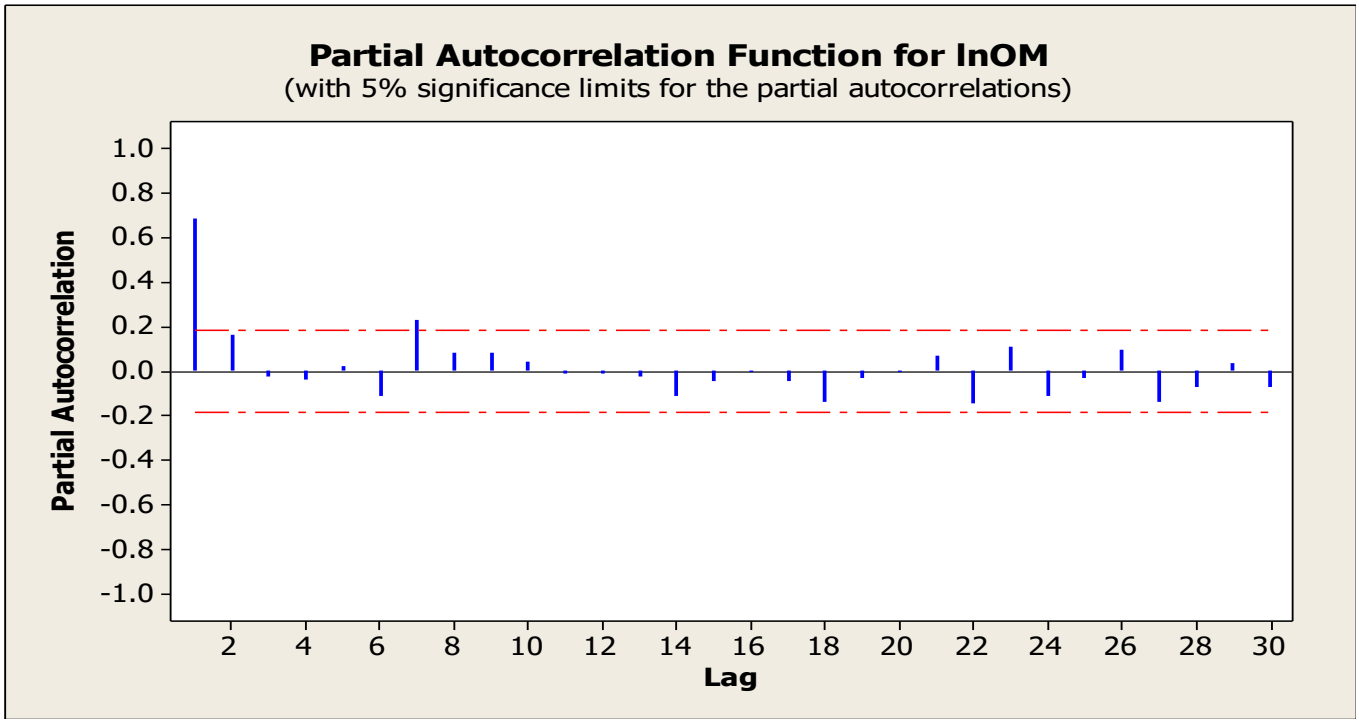

Figure 4.1.5: - SARIMA MODELS using Partial Autocorrelation Function (PACF) for Overall Malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

Table 4.1.6: - SARIMA $(0,1,1)x(0,1,1)_{12}$ model for overall malaria prevalence in the Federal

Capital Territory, Abuja from January 2009 to December 2018

Final Estimates of Parameters

Model Type	Coef	Stardard E	Test Statistic	P-Value
MA (1)	0.4998	0.0863	5.79	0.000
SMA (12)	0.8613	0.0801	10.76	0.000
CONSTANT	-0.000919	0.003763	-0.24	0.808

```
Differencing: 1 regular, 1 seasonal of order 12
Number of observations:  Original series 120, after differencing 107
Residuals:    SS =  10.4483 (backforecasts excluded)
              MS =  0.1005  DF = 104
Modified Box-Pierce (Ljung-Box) Chi-Square statistic
Lag             12     24     36     48
Chi-Square     6.9   19.7   36.6   40.9
DF               9     21     33     45
P-Value      0.645  0.538  0.307  0.644
```

Table 4.1.7: Forecasts from SARIMA $(0,1,1)x(0,1,1)_{12}$ model for overall malaria prevalence in the Federal Capital Territory, Abuja from January 2019 to December 2019

95.0 Percent				
Period	Forecast	Limits		Exponential of the forecast
		Lower	Upper	
January	7.57540	6.95403	8.19677	1950
Feb	7.67625	6.98148	8.37101	2157
Mar	7.78116	7.02004	8.54227	2396
April	7.74763	6.92551	8.56976	2317
May	7.80410	6.92518	8.68301	2451
June	7.84239	6.91015	8.77464	2546
July	7.62291	6.64022	8.60560	2045
August	7.50513	6.47446	8.53580	1817
September	7.44309	6.36658	8.51960	1708
October	7.46227	6.34179	8.58274	1741
November	7.26828	6.10550	8.43106	1435
December	7.20772	6.00412	8.41132	1350

Table 4.1.7: present the forecast from SARIMA $(0,1,1)x(0,1,1)_{12}$, shows the highest prevalence in the month of June with (2546) while the least malaria prevalence shows in the month of December, 2019 with (1350)

Time Series Decomposition of Malaria prevalence in Pregnancy women in the Federal Capital Territory, Abuja from 2009 to 2018

Table 4.2.1: The Time Series Decomposition for lnMIP (ln MIP = ln of Malaria prevalence in Pregnant women) using Multiplicative Model

Data	Length	No. of Missing value
LnMIP	96	0

Fitted Trend Equation of Malaria prevalence in Pregnancy women in the Federal Capital Territory, Abuja given as Yt = 5.59955 + 0.00824130*t

The above trend equation shows a monthly increase of 0.82% in the malaria prevalence in pregnancy in the Federal Capital Territory, Abuja for the period of January 2011 to December 2018

Table 4.2.2: Seasonal Indices of Malaria prevalence in Pregnancy women in the Federal Capital Territory, Abuja

Period(Month)	Index	Percentage (%) index	Remarks
January	0.99559	*99.56*	Decrease by 0.44%
February	0.99763	99.76	Decrease by 0.24%
March	0.99757	99.76	Decrease by 0.24%
April	1.01592	101.59	Increase by 1.09%
May	1.02536	102.54	Increase by 2.54%
June	1.01077	101.08	Increase by 1.08%
July	0.99445	99.45	Decrease by 0.55%
August	1.00254	100.25	Increase by 0.25%
September	1.01516	101.52	Increase by 1.52%
October	1.00726	100.73	Increase by 0.73%
November	0.98544	98.54	Decrease by 1.46%
December	0.95230	95.23	Decrease by 4.77%

From Table 4.2.2 above, the seasonality of prevalence malaria in pregnancy decreases in the months of January, February, march, July November, December with highest decrease of (4.77%) and increases in the month of April, May, June August September and October with highest increase of (2.54%). This is further amplified by figures 4.2.1, 4.2.2 and 4.2.3 respectively.

The highest increase number of malaria prevalence in pregnancy women was observed in the month of May with (2.54%) while the lowest decrease of malaria prevalence in pregnancy women was in the month of December with (4.77%).

Table 4.2.3: - Accuracy Measures of Malaria Prevalence in Pregnancy women from 2011 to 2018

Accuracy	MAPE	MAD	MSD
Measures	5.04065	0.29850	0.14015

Table 4.2.4: Forecasts of the malaria prevalence in Pregnancy women in the Federal Capital Territory Abuja from 2011 to 2018

Period(Month)	Forecast	Exponential of the forecast
January	6.37076	585
February	6.39202	597
March	6.39982	602
April	6.52593	683
May	6.59506	732
June	6.50954	672
July	6.41264	610
August	6.47306	647
September	6.56289	708
October	6.52010	679
November	6.38697	594
December	6.18007	483

Table 4.2.3 above shows the accuracy measure of malaria prevalence in pregnancy women while table 4.2.4 shows the forecast of the malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja. The forecast revealed a monthly

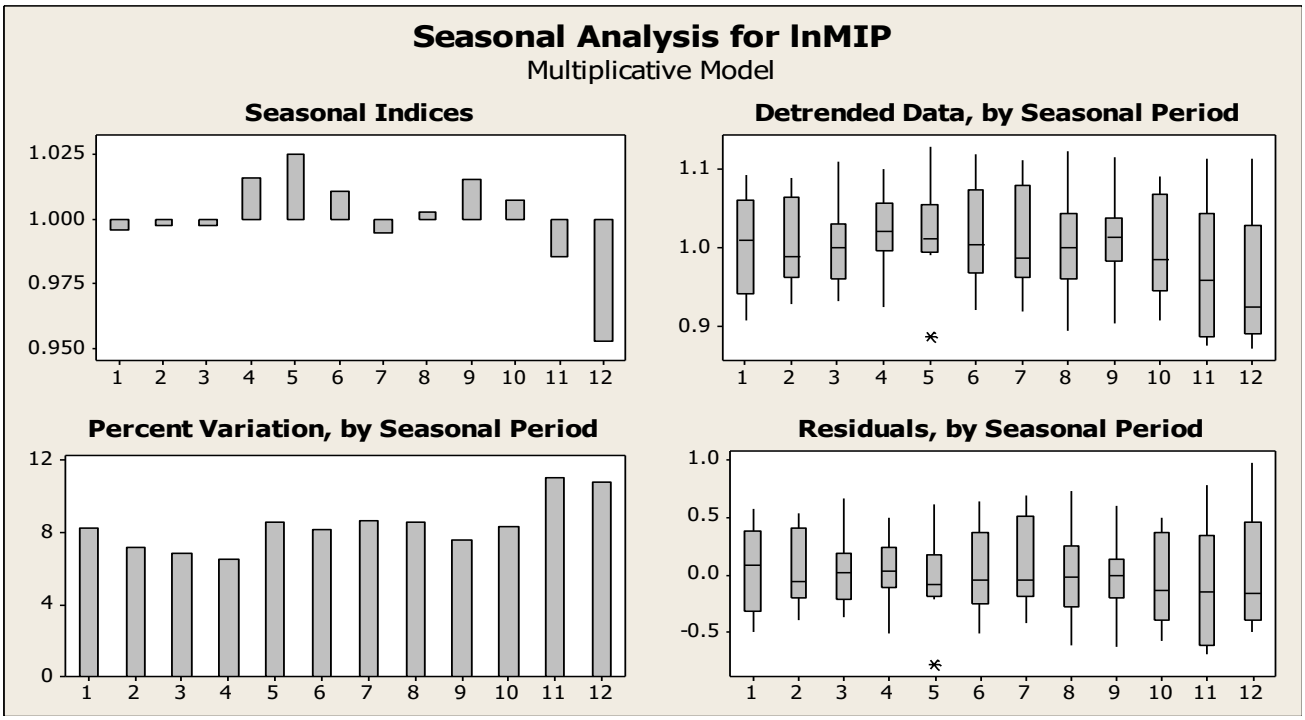

Figure 4.2.1 The Seasonal Analysis of Malaria prevalence in Pregnancy women in the FCT, Abuja from 2011 t0 2018

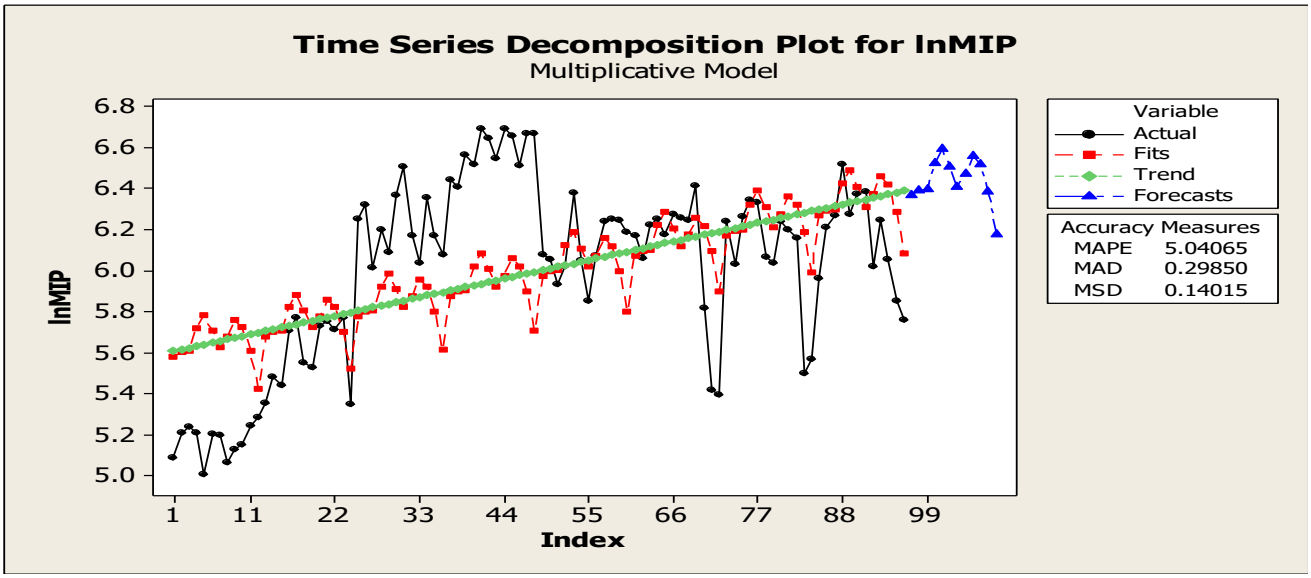

Figure 4.2.2: - Time Series Decomposition Plot for the (lnMIP) of Malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from 2011 to 2018.

The graph shows the fluctuation of malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from 2011 to 2018, although the prevalence appeared the highest occurred in the month of June and the least number was on the month of December.

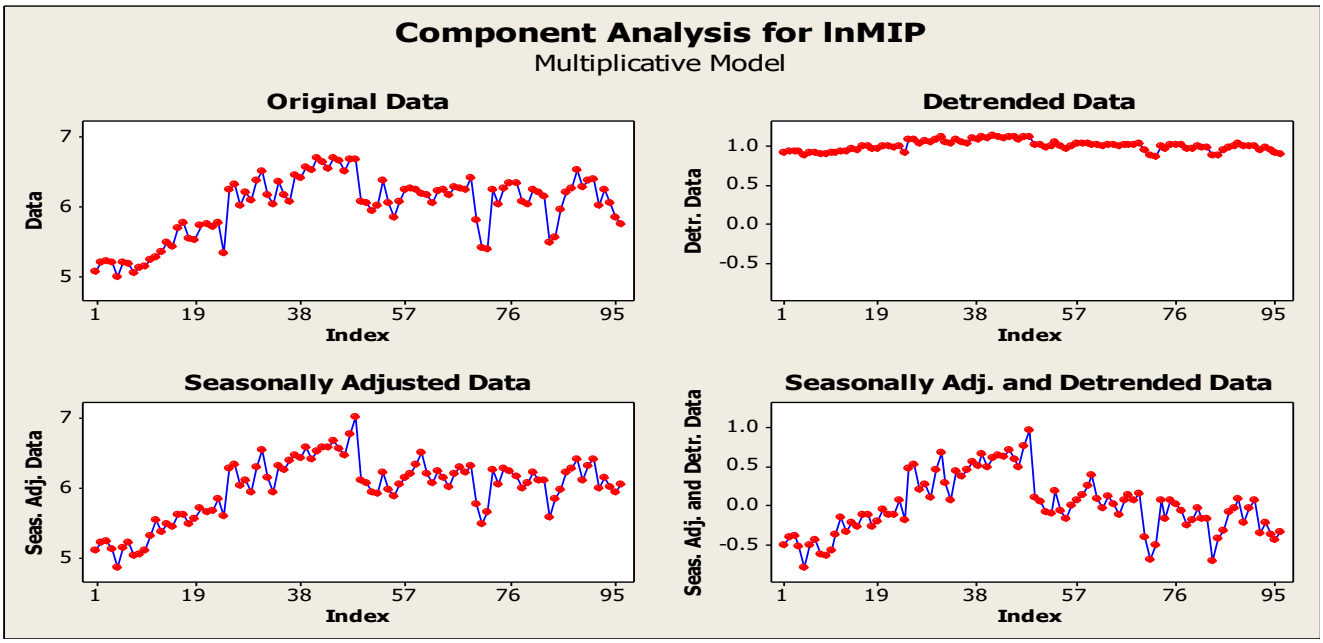

Figure 4.2.3 The Component Analysis of Malaria prevalence in Pregnancy women in the FCT, Abuja from 2011 to 2018

Table 4.2.5: The Possible SARIMA models for Malaria prevalence in Pregnancy women in the Federal Capital, Territory, Abuja

SARIMA	MSE	REMARKS
(1,1,1) X (1,1,1)	0.05357	AR is significant SAR not significant MA is significant Model not adequate
(1,1,1) X (0,1,1)	0.05306	parameter significant model not all adequate
(0,1,1) X (0,1,1)	0.06552	parameter significant model adequate except at by 24

The SARIMA (0,1,1) X $(0,1,1)_{12}$ was selected as the best model because it has the least number of parameters which are significant in the model and also the model is adequate which the evidence can be seen in the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) in the figures 4.2.4 and 4.2.5 respectively.

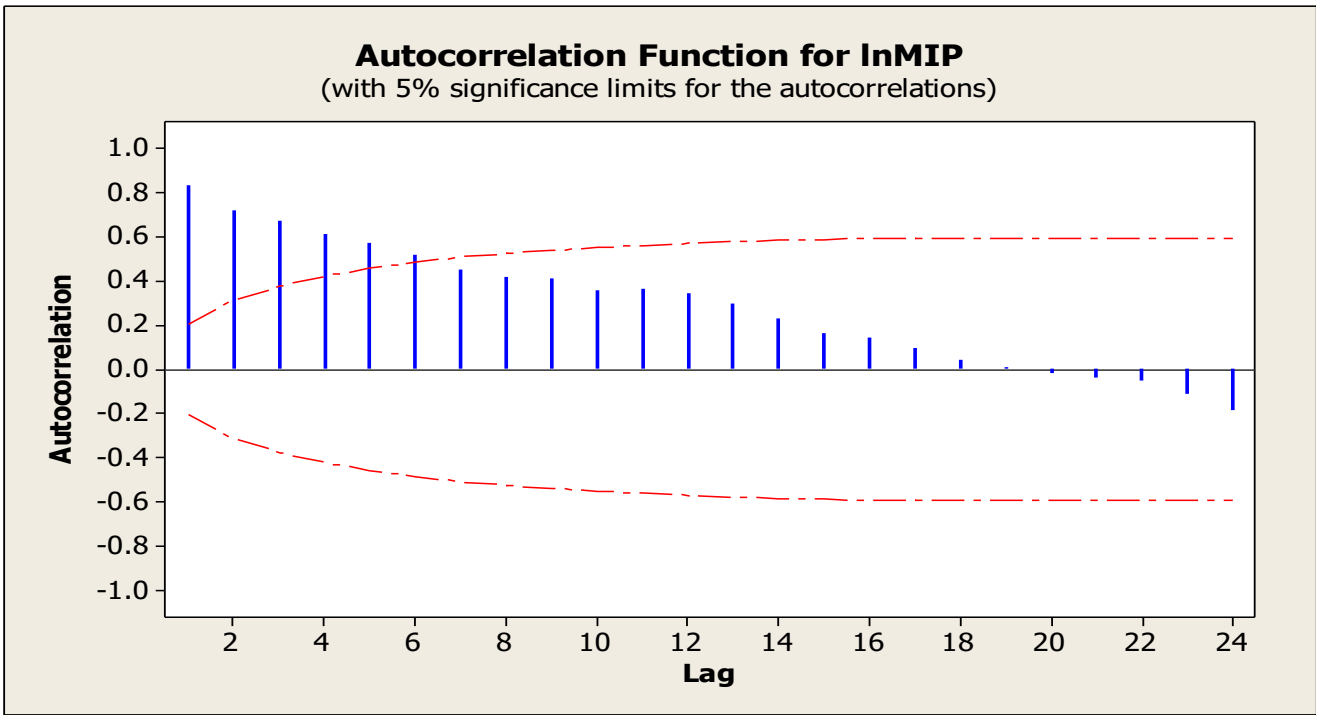

Figure 4.2.4: SARIMA Models using (ACF Autocorrelation Function for malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from 2011 to 2018

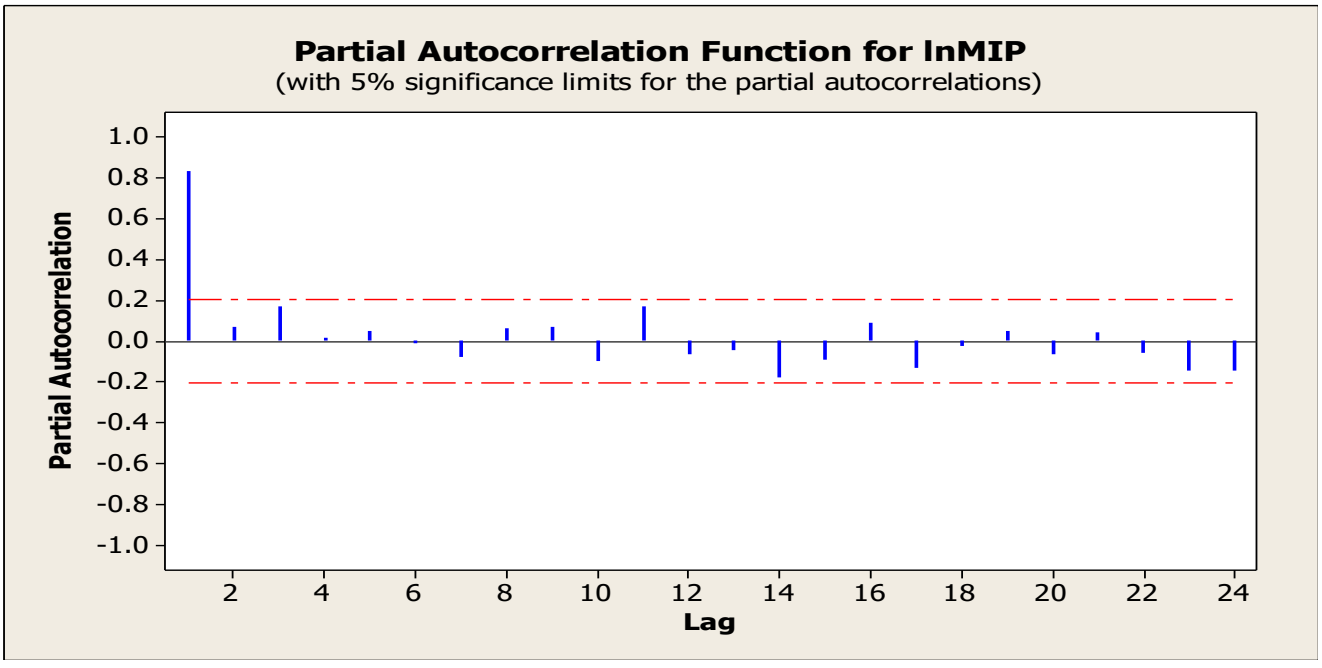

Figure 4.2.5 SARIMA Models using (PACF Partial Autocorrelation Function for malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from 2011 to 2018

Table 4.2.6: - SARIMA $(0,1,1)x(0,1,1)_{12}$ model for malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from January 2011 to December 2018

Final Estimates of Parameters

Model Type	Coef	Standard Error	Test Statistic	P-Value
MA (1)	0.3752	0.1055	3.56	0.001
SMA (12)	0.6204	0.1210	5.13	0.000
CONSTANT	-0.008918	0.007654	-1.17	0.247

```
Differencing: 1 regular, 1 seasonal of order 12
Number of observations:  Original series 96, after differencing 83
Residuals:    SS = 5.24167 (back.
forecasts excluded)
              MS =0.06552 DF = 80
Modified Box-Pierce (Ljung-Box) Chi-Square statistic
Lag             12     24     36     48
Chi-Square   13.6   38.0   46.4   56.0
DF               9     21     33     45
P-Value     0.136  0.013  0.061  0.126
```

Table 4.2.7: Forecasts from SARIMA $(0,1,1)x(0,1,1)_{12}$ model for malaria prevalence in pregnancy in the Federal Capital Territory, Abuja from January 2019 to December 2019

95.0 Percent				
Period	Forecast	Limits		Exponential of the forecast
		Lower	Upper	
January	6.09567	5.59386	6.59747	444
Feb	6.10598	5.51428	6.69768	449
Mar	6.17129	5.50165	6.84093	479
April	6.28602	5.54662	7.02543	537
May	6.19198	5.38884	6.99511	489
June	6.13595	5.27378	6.99812	462
July	6.08709	5.16968	7.00450	440
August	5.99171	5.02220	6.96122	400
September	6.07831	5.05936	7.09726	436
October	5.89033	4.82423	6.95643	362
November	5.58061	4.46936	6.69186	265
December	5.51884	4.36420	6.67347	249

From Table 4.2.7 above, present the forecast from SARIMA $(0,1,1)x(0,1,1)_{12,}$ shows the highest prevalence in the month of April (537) while the least malaria prevalence in the month of December (249)

Time Series Decomposition of malaria prevalence in Children and Adult in the Federal Capital Territory, Abuja from 2009 to 2018

Table 4.3.1: The Time Series Decomposition for lnMCA (InMCA = ln of Malaria Prevalence in Children and Adult using Multiplicative Model

Data	Length	No. of Missing value
LnMCA	120	0

Fitted Trend Equation of Malaria prevalence in children and Adult in the Federal Capital Territory, Abuja is given as $Y_t = 7.67157 - 0.00508336*t$

The above equation shows a monthly decrease of 0.51% malaria prevalence in children and Adult in the Federal Capital Territory, Abuja from January 2009 to December 2018

Table 4.3.2:-Seasonal Indices of Malaria in children and Adult in the Federal Capital Territory in the period January 2009 to December, 2018

Period(Month)	Index	Percentage (%) index	Remarks
January	0.99303	99.303	Decrease by 0.697
February	0.99629	99.629	Decrease by 0.371
March	1.00915	100.915	Increase by 0.915
April	1.01389	101.389	Increase by 1.389
May	1.00245	100.245	Increase by 0.245
June	1.01733	101.733	Increase by 1.733
July	1.01685	101.685	Increase by 1.685
August	1.00419	100.419	Increase by 0.419
September	1.00526	100.526	Increase by 0.526
October	0.98484	98.484	Decrease by 1.516
November	0.96853	96.853	Decrease by 3.147
December	0.98817	98.817	Decrease by 1.183

Summary: from table 4.3.2 above, the months of January, February, October, November and December experienced decrease of malaria prevalence in Children and Adult with

the highest decrease in the month of November (3.147%) while from the month of March to September experienced increase of malaria prevalence with highest increase of (1.733%). This is further amplified by figures 4.3.1, 4.3.2 and 4.3.3

Table 4.3.3 Accuracy Measures of Malaria Prevalence in Children and Adult from 2009 to 2018

Accuracy	MAPE	MAD	MSD
Measures	4.18957	0.31111	0.16804

Table 4.3.4 Forecasts of the malaria prevalence in children and Adult in the Federal Capital Territory, Abuja, from 2009 to 2018

Period(Month)	Forecast	Exponential of the forecast
January	7.00730	1105
February	7.02527	1125
March	7.11082	1225
April	7.13902	1260
May	7.05341	1157
June	7.15292	1278
July	7.14435	1267
August	7.05035	1153
September	7.05273	1156
October	6.90448	997
November	6.78522	885
December	6.91775	1010

The forecast in table 4.3.4 above, revealed a fluctuation in the children and Adult malaria prevalence in the Federal Capital Territory, Abuja for the year 2019.Although

there was higher increase in the month of July with (1267) and lower decrease in the month of November with (885)

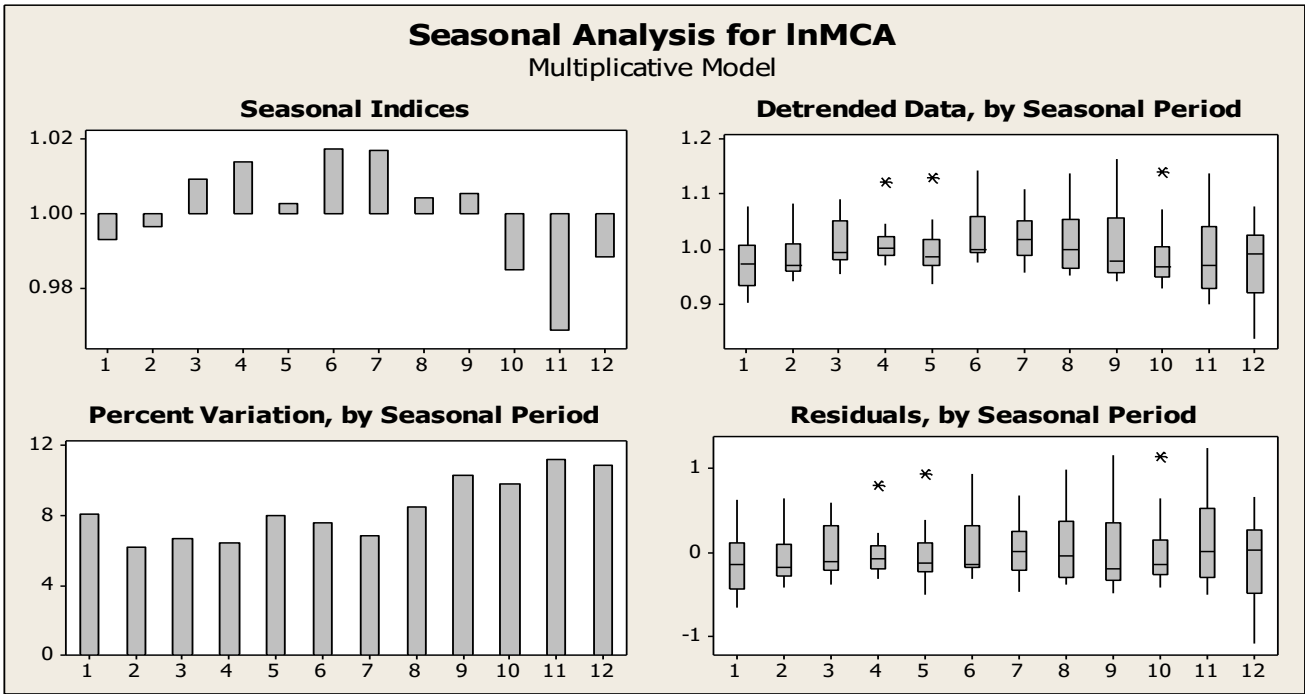

Figure 4.3.1: The Seasonal Analysis of Children and Adult malaria prevalence in the Federal Capital Territory, Abuja from 2009 to 2018

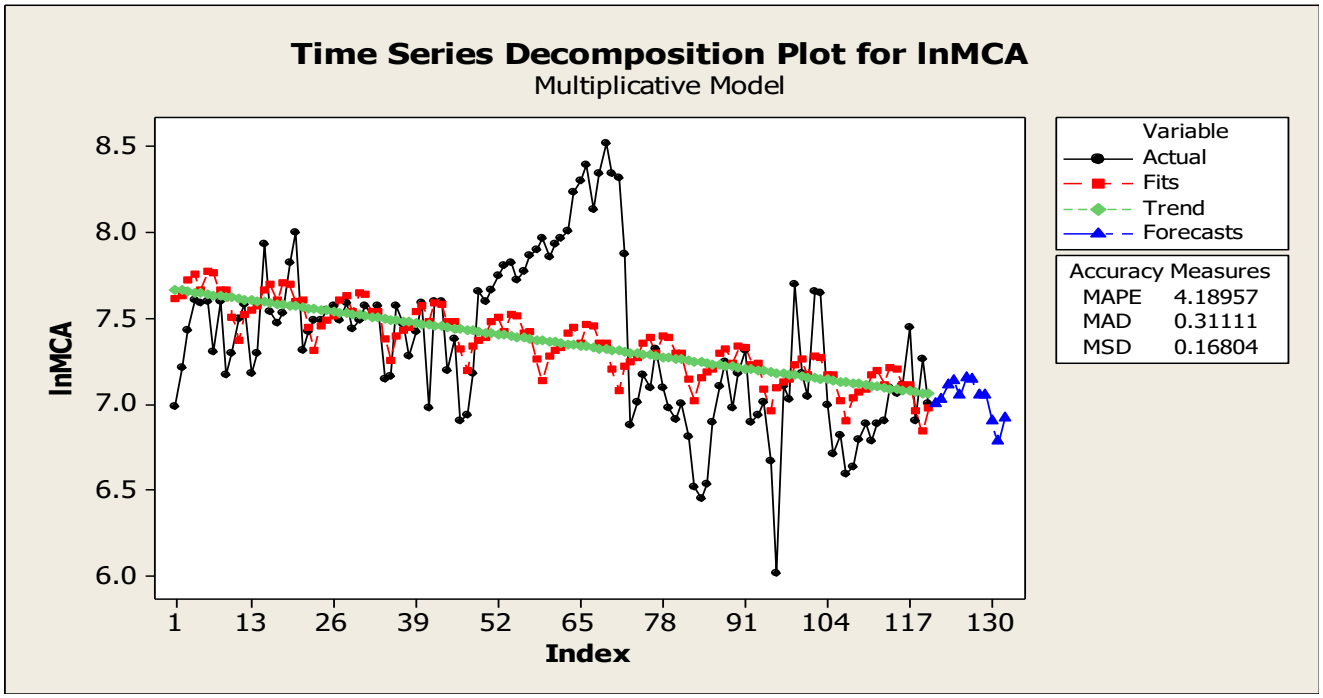

Figure 4.3.2: Time Series Decomposition for Malaria prevalence in Children and Adult

Summary: - The graph shows the fluctuation of malaria prevalence in children and Adult, although the prevalence appeared highest in the month of June and the lowest in the month of December

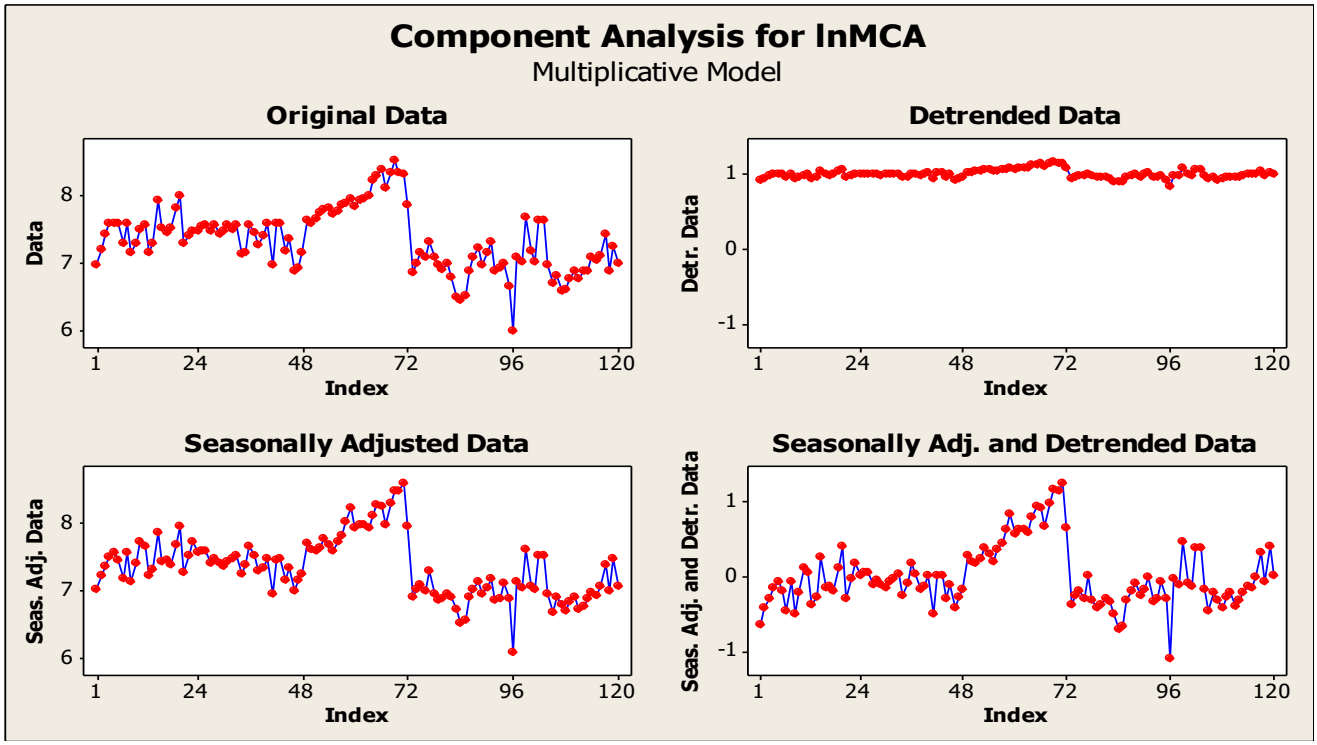

Figure 4.3.3: The Component Analysis of Malaria Prevalence in Children and Adult in the Federal Capital Territory, Abuja from 2009 to 2018.

Table 4.3.5: possible SARIMA models for Malaria prevalence in Children and Adult in the Federal Capital Territory, Abuja from 2009 to 2018

SARIMA	MSE	REMARKS
(1,1,1) X (1,1,1)	0.08650	AR, SAR not significant MA, SAR significant Model adequate
(0,1,1) X (0,1,1)	0.1043	MA, SMA significant and Adequate

The SARIMA (0,1,1) X $(0,1,1)_{12}$ was selected as the preferred model because it has the least number of parameters which are significant in the model and the model is also

adequate. The evidence can be seen in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in the figures 4.3.4 and 4.3.5

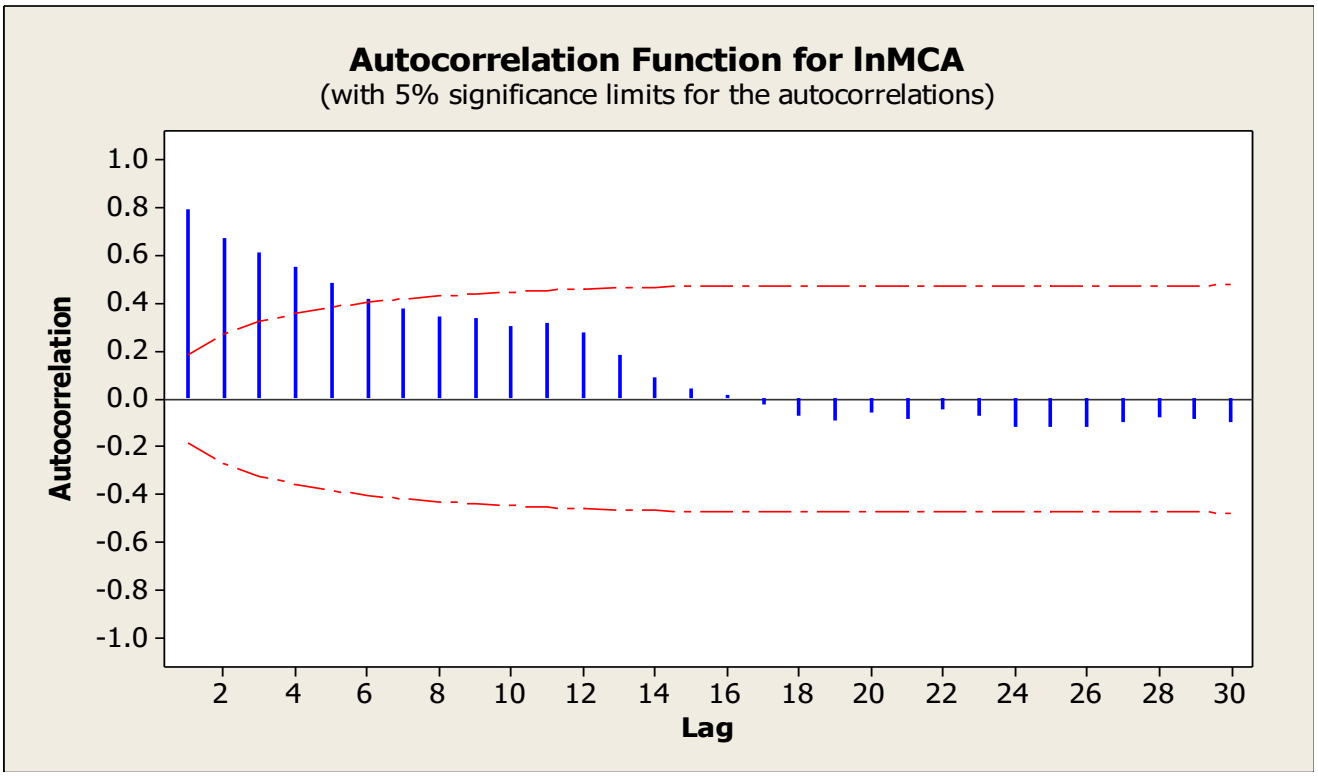

Figure 4.4.4: - SARIMA Models using Autocorrelation Function (ACF) for malaria prevalence in children and adult in the Federal Capital Territory, Abuja from 2009 to 2018

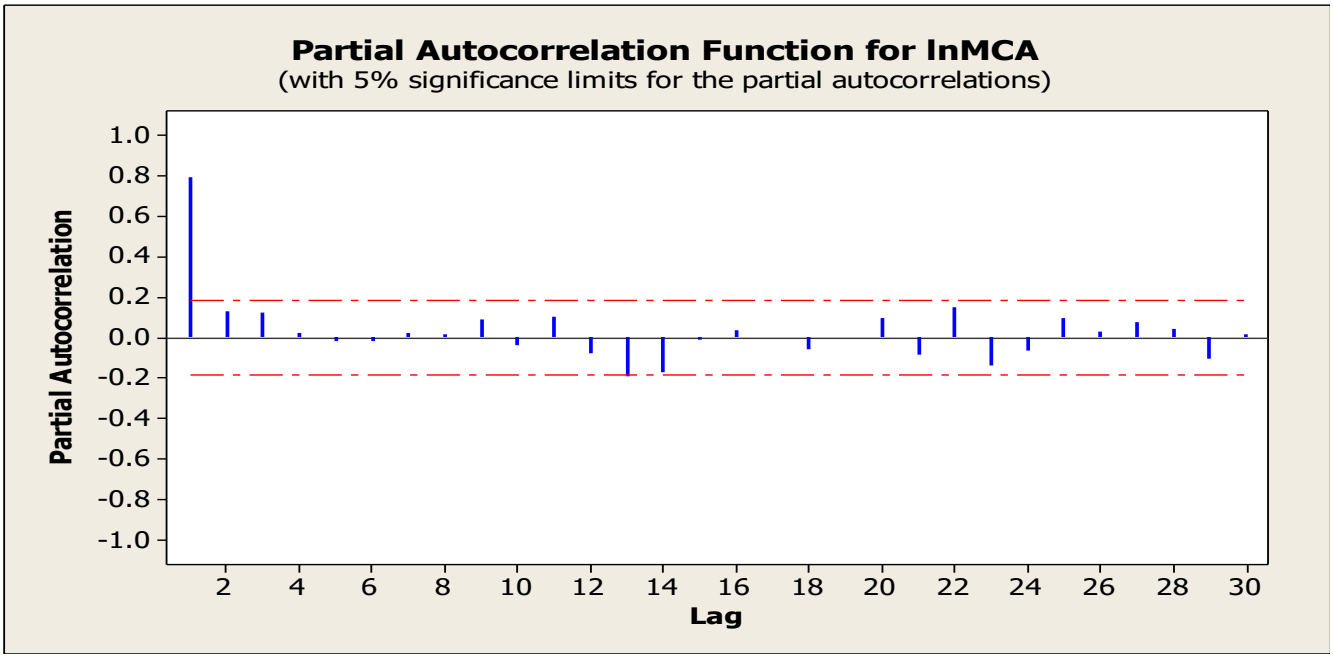

Figure 4.4.5: - SARIMA Model using Partial Autocorrelation Function (PACF) for malaria prevalence in children and adult in the Federal Capital Territory, Abuja from 2009 to 2018

Table 4.3.6SARIMA (0,1,1) x $(0,1,1)_{12}$ model for malaria prevalence in children and Adult in the Federal Capital Territory, Abuja from January 2009 to December 2018

Final Estimates of Parameters

Model Type	Coef	Standard Error	Test Statistic	P-value
MA(1)	0.2888	0.0964	3.00	0.003
SMA(12)	0.5500	0.1011	5.44	0.000
CONSTANT	0.00112	0.01074	0.10	0.917

```
Differencing: 1 regular, 1 seasonal of order 12

Number of observations:  Original series 120, after differencing 107

Residuals:    SS =  10.8420 (backforecasts excluded)

              MS =  0.1043  DF = 104

Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag             12     24     36     48

Chi-Square     7.4   30.0   40.8   51.7

DF               9     21     33     45

P-Value      0.591  0.093  0.164  0.230
```

Table 4.3.7 Forecasts from SARIMA $(0,1,1)x(0,1,1)_{12}$ model for malaria prevalence in children and adult in the Federal Capital Territory, Abuja from January 2009 to December 2018

Forecasts from period 120 and 95.0 Percent				
Period	Forecast	Limits		Exponential of the forecast
		Lower	Upper	
January	7.27535	6.64238	7.90832	1444
Feb	7.36129	6.58457	8.13801	1574
Mar	7.53532	6.63758	8.43306	1873
April	7.47752	6.47324	8.48181	1768
May	7.42864	6.32808	8.52920	1684
June	7.69349	6.50443	8.88255	2194
July	7.67866	6.40723	8.95008	2162
August	7.48638	6.13761	8.83514	1784
September	7.58692	6.16502	9.00882	1972
October	7.35153	5.86007	8.84299	1559
November	7.39419	5.83628	8.95211	1627
December	7.18088	5.55923	8.80253	1314

Table 4.3.7 present the forecast from SARIMA (0,1,1) x (0,1,1)12 shows the highest prevalence of malaria in the month of June with (2194) while the least malaria prevalence shows in the month of December with (1314).

Table 4.4.1: Test of over dispersion of the malaria prevalence in the Federal Capital Territory, Abuja from January, 2009 to December, 2018

```
. summarize OM MIP MCA

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          OM |        120    2110.608    992.6839         625       5074
         MIP |         96    441.1146    174.1108         149        810
         MCA |        120    1756.883    871.1392         410       5013
```

The descriptive statistic in Table 4.4.1 above, shows evidence of over dispersion since the variances are greater than the means. In such situation negative binomial regression model is proposed.

Table 4.4.2: Trend analysis of overall malaria prevalence in the Federal Capital Territory, Abuja from January 2009 to December 2018 using negative binomial regression model

```
Negative binomial regression OM                         Number of obs      =
120
                                                  LR  chi2(1)               =
1.19
Dispersion      = mean                             Prob > chi2        =
0.2762
Log likelihood = -981.07166                        Pseudo R2          =
0.0006
------------------------------------------------------------------------------
--
          OM |        Coef.    Std. Err.        z     P>|z|       [95% Conf.
Interval]
-------------+----------------------------------------------------------------
--
        Time |   -.0013809     .0012652      -1.09     0.275      -.0038606
.0010988
       _cons |    7.735954     .0851347      90.87     0.000       7.569093
7.902815
-------------+----------------------------------------------------------------
--
    /lnalpha |   -1.66425    .1255651                          -1.910353    -
1.418147
-------------+----------------------------------------------------------------
--
       alpha |    .1893326    .0237736                           .1480281
.2421623
------------------------------------------------------------------------------
--
LR test of alpha=0: chibar2(01) = 4.9e+04                Prob >= chibar2 =
0.000
```

The result in table 4.4.2 above shows a negative trend (Time= -0.0014) in the overall malaria prevalence in the Federal Capital Territory Abuja, although not significant (p-value=0.275>0.05).

Table 4.4.3: Trend analysis of malaria in Children and Adult in the Federal Capital Territory, Abuja from January 2009 to December 2018 using negative binomial regression

```
Negative binomial regression(MCA)                Number of obs     =        120
                                                 LR chi2(1)        =      12.57
Dispersion     = mean                            Prob > chi2       =     0.0004
Log likelihood =  -957.4124                      Pseudo R2         =     0.0065
------------------------------------------------------------------------------
         MCA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Time |  -.0045639   .0012543    -3.64   0.000    -.0070222   -.0021056
       _cons |   7.732507    .084456    91.56   0.000     7.566976    7.898038
-------------+----------------------------------------------------------------
    /lnalpha |  -1.674837   .1256709                     -1.921147   -1.428527
-------------+----------------------------------------------------------------
       alpha |   .1873387    .023543                      .1464388    .2396618
------------------------------------------------------------------------------
LR test of alpha=0: chibar2(01) = 4.2e+04             Prob >= chibar2 = 0.000
```

The result in table 4.4.3 above shows a negative trend (Time= -0.0046) in the malaria prevalence in children and adult in the Federal Capital Territory, Abuja and the trend is significant (p-value=0.000<0.05).

Table 4.4.4: Trend analysis of malaria prevalence in pregnancy women in the Federal Capital Territory, Abuja from January 2009 to December 2018 using negative binomial regression

```
Negative binomial regression(MIP)                Number of obs     =         20
                                                 LR chi2(1)        =       0.03
Dispersion     = mean                            Prob > chi2       =     0.8573
Log likelihood = -122.97456                      Pseudo R2         =     0.0001
------------------------------------------------------------------------------
         MIP |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Time1 |  -.0017836   .0099178    -0.18   0.857    -.0212222    .0176549
       _cons |   6.151701   .1095657    56.15   0.000     5.936956    6.366446
-------------+----------------------------------------------------------------
    /lnalpha |  -2.805859   .3253933                     -3.443618     -2.1681
-------------+----------------------------------------------------------------
       alpha |   .0604548   .0196716                      .0319489    .1143947
------------------------------------------------------------------------------
LR test of alpha=0: chibar2(01) = 458.22              Prob >= chibar2 = 0.000
```

The result in table 4.4.4 above shows a negative trend (Time= -0.0018) in the malaria prevalence in Pregnancy women in the Federal Capital Territory, although not significant (p-value=0.857>0.05).

4.3 **Discussion of Results**

From Table 4.1.1, 4.2.1 and 4.3.1 showed fitted Trend Equation of overall total number of Malaria prevalence, malaria prevalence in pregnancy women and Malaria prevalence in children and Adult in the Federal Capital Territory, Abuja given as: Y_t = 7.62582 - 0.00112517*t, Yt = 5.59955 + 0.00824130*t and Y_t = 7.67157 - 0.00508336*t respectively.

The above trend equations showed a monthly decrease of 0.11% and 0.51% in the overall malaria incidence cases and the malaria prevalence in children and adult in the Federal Capital Territory, Abuja while the research revealed that malaria prevalence in pregnancy women increased with 0.82% for the period of January 2009 to December 2018.

From the table 4.1.2 above, the month of January to July experienced an increased prevalence of malaria with highest prevalence in the month of June with (3.6%) while in the month of August to December experienced decrease of malaria prevalence with lowest prevalence in the month of December (7.6%) and this can be further amplified by Figures 4.1.1, 4.1.2 and 4.1.3 but in the case of children and adult malaria prevalence in table 4.3.2 above, the months of January, February, October, November and December experienced decrease which occurred lowest in the month of November with (3.147%) while from the month of March to September experienced increase of malaria prevalence with highest increase of (1.733%) in the month of June and it further amplified by figures 4.3.1, 4.3.2 and 4.3.3

From table 4.1.5, 4.2.5 and 4.3.5 showed possible SARIMA $(0,1,1)x(0,1,1)_{12}$ as the preferred model because it has the least number of parameters which are significant in the model and also the model is adequate as well as evidence can be seen in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in the Figures 4.1.4. and 4.1.5 respectively.

The Autocorrelation Function (ACF) plots of the transformed malaria cases of data in figure 4.1.4 showed a depict seasonality, which dies down slightly, while the Partial Autocorrelation Function (PACF) plots of the malaria cases of data in figure 4.1.5 tail off after lag 1 and decays in sine-wave fashion in an initial attempt to remedy the non-stationary of the time series, and eliminate the trend and seasonality.

Table 4.1.7, 4.2.7 and 4.3.7 present the forecast of SARIMA $(0,1,1)x(0,1,1)_{12}$, with the highest overall malaria prevalence in the month of June with (2546) while the least malaria prevalence in the month of December with (1350) but in the side of malaria prevalence in pregnancy women showed the highest in the month of April with (537) and the lowest prevalence in the month of December with (249) and more so, the forecast revealed that the highest malaria in children and adult incidence occurred in the month of June with (2194) and least was in the month of December with (1314)

The Test of over dispersion was conducted and Negative Binomial Regression Model was proposed since descriptive statistic in Table 4.4.1 above, shows evidence of over dispersion, that is, the variances are greater than the means of malaria prevalence in the Federal Capital Territory, Abuja from January, 2009 to December, 2018

The results in table 4.4.2, 4.4.3 and 4.4.4 above showed a negative trend (Time= -0.0014, -0.0046 and -0.0018) in the overall malaria prevalence, malaria prevalence in children and adult as well as malaria prevalence in pregnancy women with their P-Values although overall malaria incidences was not significant with p-value = 0.275>0.05) but in children and adult trend is significant since p-value = 0.000<0.05) and also not significant in malaria prevalence in pregnancy women because p-value = 0.857>0.05

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This study was conducted to investigate the time and period of the year that malaria prevalence is either on the increase or decrease in the Federal Capital Territory and the effect of seasonal variation on malaria with the use of time series analysis from 2009 to 2018. It was found that the reported cases of overall Malaria prevalence and malaria prevalence in children and adult were decreased but that of malaria prevalence in pregnancy women was on an increase in the Federal Capital Territory based on the years under review and a total number of 253273 malaria prevalence cases were reported from January 2009 to December 2018. The report of 210826 and 42447 were recorded for malaria prevalence in children and adult as well as malaria prevalence in pregnancy women.

This study has demonstrated that time-series predictions are generated by models based on changes over time in previously observed values or historical datasets. The SARIMA forecast model can serve as useful tools for public health researchers and epidemiologists. It can be applied as a malaria early-warning system and, can provide vital information to enable the relevant authority to act proactively. This study shows how the Negative Binomial Regression and SARIMA model (which is particularly relevant for a disease that exhibits seasonality as in the case of this study) was useful in modeling and forecasting malaria cases in the Federal Capital Territory, Abuja between 2009 and 2018.

5.2 Conclusions

Malaria is transmitted through the bite of an infected female Anopheles mosquito, which usually feeds between sunset and sunrise. The Anopheles itself becomes infected by taking in parasites after feeding on infected human blood. The parasites then develop inside the mosquito and about a week later can be transferred to a new host when the mosquito feeds again. Young children and Pregnant Women are at the highest risk of malaria infectious and mortality. Many children experience initial malaria infection during their first two years of life, when they have not yet developed sufficient immunity, making this early year particular dangerous.

The development of predictive models is a vital part of malaria surveillance, enabling policymakers and public health workers to project the future occurrence of the disease and act proactively. Therefore, the Federal Ministry of Health together with the health workers should intervene in the creation of awareness of this silent killer disease. Although the model also proved that the model is adequate for forecasting of monthly reported cases of malaria infectious in the Federal Capital Territory, Abuja and the forecast was also found to have an oscillatory trend for some time and then remain constant for some period. Moreover, the model was found to have a possible SARIMA (0, 1, 1) (0,1, 1). Therefore, hospitals in the Federal Capital Territory should expect a reduction in the number of malaria cases in the coming years as shown on the forecast graphs.

5.3 Recommendations

Based on the findings and conclusion of this study, the research recommends that Government should:

1. The Federal Ministry of Health and its workers should carry out campaign awareness against this malaria, since the trend indicated that 0.11% and 0.51%

shows monthly decrease in overall malaria prevalence, children and adult malaria reported cases

2. The pregnant women generally, should be encouraged to attend Antenatal Care (ANC) since the result revealed that there was an increase of 0.82% in Malaria incidence cases.
3. The Federal Capital Territory Administration should inoculate her residence and fumigate the environment at least Quarterly.
4. The removal of blocked drainages and environmental cleanliness within the Federal Capital Territory, Abuja.

5.4 Limitations of the Study

The weakness of the study is that it attempted to develop a single model for entire malaria reported cases in the Federal Capital Territory, Abuja. And the process of data collection from the sources was a big task to the researcher due to administrative bureaucracy associated with data collection in public and private organizations as well as, the financial involvement during this process of gathering data, analysis are the great challenges to the researcher.

5.5 Suggestion for Further Study

Further research should be carried out on Time Series Analysis on the trend and seasonality of reported cases of malaria prevalence in the Federal Capital Territory, Abuja

5.6 Contributions to Knowledge

a. The study will make the Government introduce the usage of mosquitoes treated nets and insecticides.
b. This will guide the Government in formulating policies on malaria infectious control

c. This knowledge will guide other researchers who want to embark on further study on malaria-endemic

d. The study has created awareness to the general public on the control of malaria infectious.

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APPENDIX

Table

Table 5: A total summary of reported cases of overall malaria prevalence, malaria prevalence in pregnancy women and total number of malaria prevalence in children and Adult in the Federal Capital Territory, Abuja from 2009 to 2018.

Yearly Statistics			
Years	(MCA)	(MIP)	OMI
2009	20157	0	20157
2010	23347	0	23347
2011	21333	2114	23447
2012	18208	3275	21483
2013	28964	6072	35036
2014	44481	8752	53233
2015	12710	5494	18204
2016	12515	5379	17894
2017	15547	5428	20975
2018	13564	5933	19497
Total	**210826**	**42447**	**253273**

MCA = Malaria prevalence in Children and Adult

MIP = Malaria prevalence in pregnancy women

OMI = Overall Malaria Infectious

DMI = Deaths occurred during Malaria Infectious

Sources: National Bureau of Statistics, from 2009 to 2018.