Investigating Malaria Incidence Trends and Gender Independence: A Case Study of General Hospital, Ota, Ogun State (2016-2019) Using ARIMA Analysis

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Abstract:

Malaria in Sub-Saharan African countries is one of the three major factors that can lead to shifts in population size, which is death. Due to the high risk of this disease in Sub-Saharan and Nigeria in particular, this project investigates the incidence of malaria among patients that came to General Hospital, Ota from January 2016 to December 2019 to identify an appropriate statistical model that can be used to describe the trend of malaria and make future projections of the disease in Ogun state, General Hospital, Ota, which will serve as a guide to policymakers in reducing the incidence of malaria. The Autoregressive Integrated Moving Average (ARIMA) method was used to estimate the trend of malaria and the trend line equation obtained shows a gradual upward trend for malaria. 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 malaria that is malaria is not gender sensitive. Correlation analysis conducted shows that there is strong relationship between cases of malaria in males and females. Based on the Pearson correlation which is 0.991 A positive relationship indicates two variables moving in the same direction (as the Male cases of malaria increase, female cases of female cases also increase). This result indicates that the occurrence of the diseases is independent on gender, and one gender is not more susceptible to Malaria than the other.

Keywords: Malaria, Correlation Analysis, Time Series Analysis, ARIMA, Chi Square Test

1.0 Introduction

The name, malaria, derives from the medieval Italian words for bad air-malaria. The then widely held miasma theory of humoral medicine attributed many infectious diseases to the presence of foul or corrupt air, poisoned by noxious vapors produced by putrefying materials. (Dagen, 2020; Singh et al., 2024). Malaria is a major public health problem in developing countries and is the top-ranked priority tropical disease of the World Health Organization. Plasmodium parasites, which cause malaria, are spread to humans by the bites of Anopheles mosquitos carrying the infection. Humans can contract parasites from five different species: P. *falciparum, P. vivax, P. ovale, P. malariae, and P. knowlesi. P. vivax* and *P. falciparum* are the most common of them, with P. falciparum being the most harmful (Del et al., 2014; Adekola et al., 2023).

In Nigeria, malaria accounts for more than 50% of outpatient visits and 40% of hospital admissions, making it a serious public health problem, particularly for children under five. Additionally, it contributes significantly to maternal and newborn mortality, accounting for 30% and 25% of deaths, respectively. The number of malaria cases globally has been increasing in recent years, with Africa having the highest burden of cases. In 2017, there were 219 million malaria cases and 435,000 deaths globally. The WHO aims to reduce malaria mortality and morbidity by at least 40% by 2020, but progress has slowed down (Ivana et al., 2019) Despite extensive efforts to control it, malaria remains a threat to millions worldwide (World Health Organization, 2020; Singh et al., 2024).

There are estimated one million deaths each year, with nearly seventy-five percent (75%) occurring in children living in sub-Saharan Africa. Nigeria has launched the Roll Back Malaria initiative to address this problem (Seun-Addie, 2015).

Malaria being major health challenges generated a lot of health challenges nationwide (Nigeria) since it contributes to one of the three major factors that can lead to shifts in population size which is death, which can lead to a decrease in the population size of the country affecting people of all ages and genders with a high number of cases reported each year. It can have a significant impact on individuals, families, and communities, leading to illness, hospitalizations, and even death if not properly managed. Despite efforts by individuals, government, and non-governmental organizations (NGOs) in curbing this menace, it still poses a lot of threat to society as such this research work aims to ascertain the level at which their efforts through the years have reduced the level of the occurrence of these diseases (Adekola et al., 2023).

If left untreated, they can lead to severe complications and even be life-threatening. Similarly, Regular check-ups, adherence to medication, and lifestyle modifications can play a crucial role in managing these conditions and improving overall well-being, Efforts are being made to address these health challenges in Nigeria through public health initiatives, education, and access to healthcare services. Individuals need to be aware of the risks, take preventive measures, and seek appropriate treatment if affected.

The problem we aim to address in this investigation is to understand the prevalence, association, and future impacts of this particular disease in a specific population. By examining these factors, we can identify strategies for prevention, improve treatment approaches, and enhance overall healthcare outcomes for individuals affected by the disease, we want to identify any potential correlations, patterns, or future occurrences of this disease. The aim of this study is to investigate the incidence of malaria among patients at General Hospital, Ota, from January 2016 to December 2019, and to identify an appropriate statistical model for describing malaria trends and making future projections in Ogun State. This will provide valuable insights for policymakers to develop effective strategies for reducing the incidence of malaria in the region under study.

2.0 Materials and Methods

2.1 Chi Square Statistic

The data utilized for this study, in other to achieve the aim and objectives is primary data which is reported cases of patients admitted in the hospital (Ogun State General Hospital, Ota) for a period of 4 years. The chi-square test will be carried out to determine the association of this disease genderwise. The chi-square test statistic is expressed as:

$$\chi^2 = \sum\sum\frac{\left(o_{ij} - \mathrm{E}_{ij}\right)^2}{\mathrm{E}_{ij}} \qquad \text{...(1)}$$

Where:

o_{ij}: is the observed cell count in the i_{th} row and j_{th}column of the table

E_{ij}: is the expected cell count in the i_{th} row and j_{th}column of the table, computed as:

$$\mathrm{E}_{ij} = \frac{i_{th}rowtotal \times j_{th}columntable}{GrandTotal} \qquad \text{...(2)}$$

The Hypothesis to be tested:

H_o: There is no association between gender and diseases.

H_1: There is an association between gender and diseases.

2.2 Correlation Analysis

Correlation analysis will be carried out to determine the degree and direction of the relationship between male and female who are affected by the diseases. Pearson's Correlation will be used and its stated as:

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \quad \text{..(3)}$$

r_{xy} = Pearson r correlation coefficient between x and y

n = number of observations

x_i = value of x (for ith observation)

y_i = value of y (for ith observation)

2.3 Time Series Analysis

Furthermore, time series analysis was used to determine the trend of this disease and forcast future occurrences. Descriptive statistics were used to generate trends over the study period under review. To ascertain which quarter of the year experienced the highest number of reported cases of malaria patients, a multiplicative time series model is adopted to examine the trend. The model is

$Y_t = T_t * S_t * C_t * I_t$………………. …………………………………………………(4)

Where; Y_t the observed value of the time series in time t,$T_t$is the trend component in time t; $S_t$is the seasonal component in time t; $C_t$is the cyclical component n time t, and $I_t$is the irregular component in time t. If the parameters C_t and $I_t$are assumed to be constant and1. Thus, by making $S_t$the subject, equation * becomes

$S_t = \frac{Y_t}{T_t}$……………………………………………………………………………(5)

Average seasonal variation by quarter (ASVQ) was estimated as

ASVQ= $\sum_{i=1}^{n}((\frac{Y_t}{T_t})x100)$/ni

Where Y_t is observed

2.3.1 Autoregressive Integrated Moving Average (ARIMA)

ARIMA models were developed to forecast malaria incidence by leveraging temporal autocorrelation in the data. The dataset was divided into a training period (January 2016 to December 2019) for developing the ARIMA models and a validation period (January 2020 to December 2025) to test their predictive accuracy. ARIMA models provide n-step-ahead predictions based on temporal dependencies in time series data. The notation (p,d,q) × (P,D,Q)S describes the temporal patterns used for forecasting, including autocorrelation over p months or P periods (each period being 12 months), differencing over d months or D periods, and moving averages over q months or Q periods (Box, 2013).

To identify the patterns best describing malaria incidence, the Box-Jenkins approach was used, consisting of three steps. First, the time series of malaria incidence was plotted to detect and correct for non-stationarity. Autocorrelation (ACF) and partial autocorrelation (PACF) functions were calculated to identify necessary autoregressive and moving average terms. Second, models of varying orders were fitted and compared using the Akaike information criterion (AIC) to balance fit improvement and model complexity. Third, the Ljung-Box test confirmed the absence of temporal autocorrelation in model residuals (Burns, 2002).

The goal was to determine which model performed better for real-time short-term surveillance versus longer-term (up to yearly) malaria prediction. Forecast accuracy was evaluated by calculating the mean square error (MSE) and the predictive R2, which indicates the proportion of variance explained by the model. Predictive R2 values range from negative values (indicating poor model performance) to values approaching one (indicating high explanatory power). Model forecasts and 95% prediction intervals were plotted against observed data from January 2016 to December 2019. Additionally, the incorporation of meteorological and environmental variables was evaluated for their potential to improve model fit and forecasting accuracy. Using the “Naïve method” approach, predictors were selected to determine their association with malaria incidence after adjusting for shared temporal patterns. ARIMA models were fitted to each climatic predictor, and cross-correlation functions between residuals of climate and malaria models identified significant lags. These lags were then incorporated into the base ARIMA model as external regressors (Alegana et al., 20214).

The models, with external regressors, were used for both short- and long-term predictions. Forecasts of regressors were integrated into the malaria prediction models for predictive horizons exceeding the available data on these variables. The analyses were conducted using the R statistical package (R Core Development Team, Vienna) and SPSS statistical package.

3.1 Results

This section shows presentation of data, its analysis and the results of our study. Figure 1 is a bar chart of the Total Number of Malaria Cases by Month from 2016 to 2019. Each bar on the chart represents a month, and the height of the bar shows the total number of malaria cases during the month. By looking at this chart you can easily compare the number of cases across different months and see if there is any noticeable trend or pattern over the four years. It is a simple yet effective way to get a clear view of the malaria situation throughout those years.

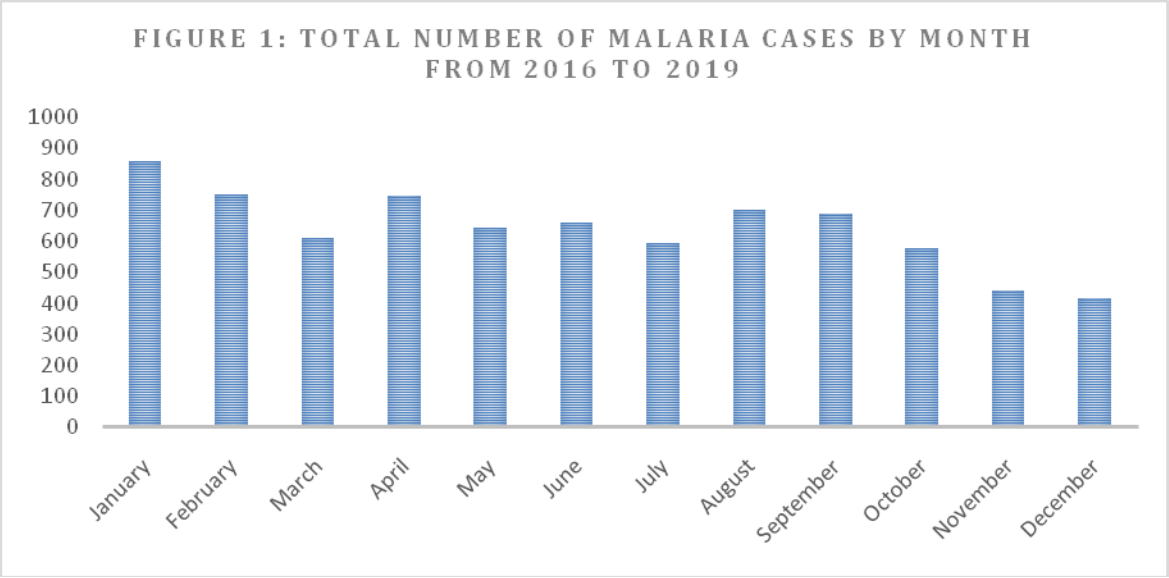


Figure 1: Total Number of Malaria Cases by Month from 2016 to 2019

We went further to perform chi square test to show if there is relationship between malaria based on gender

Table 1: Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1740.000[a]	1677	.139
Likelihood Ratio	338.364	1677	1.000
Linear-by-Linear Association	39.618	1	.000
N of Valid Cases	48		

a. 1760 cells (100.0%) have expected count less than 5. The minimum expected count is .02.

The hypothesis tested is:

H_o: There is no significant association between the gender and malaria cases

H_1: There is a significant association between the gender and malaria cases

The p-value of 0.139 is greater than 0.05 indicating a not statistical significance as shown in table 1. we hereby conclude and accept the null hypothesis (H_o) and reject the alternative hypothesis(H_1), indicating there is no relationship between gender and cases of malaria.

3.2. Correlation between Malarias in male and female

We want to see the strength of relationship with regards to gender

Table 2: Correlations between Malarias in male and female

		Sex	sex
Sex	Pearson Correlation	1	.991**
	Sig. (2-tailed)		.009
	N	4	4
Sex	Pearson Correlation	.991**	1
	Sig. (2-tailed)	.009	
	N	4	4

**. Correlation is significant at the 0.01 level (2-tailed).

It was observed that that there is strong relationship between male and female malaria cases that is increase in malaria in male also results to increase in malaria in females as revealed in table 2. Based on the Pearson correlation which is 0.991 A positive relationship indicates two variables moving in the same direction (e.g., as the Male cases of malaria increase, Female cases of female cases also increase). This result indicates that the occurrence of the diseases is independent on gender, and one gender is not more susceptible to Malaria than the other.

3.3 Trend Analysis - Malaria Cases

Table 3: Trend Analysis Result for the Malaria Cases

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	161610.958	26345.543		6.134	.000
	Year	-80.025	13.059	-.670	-6.128	.000

a. Dependent Variable: Malaria

Malaria Fever = 161,610.958 – 80.025(Year)

3.3.1. Trend Plot of Malaria Cases Between 2016 to 2019

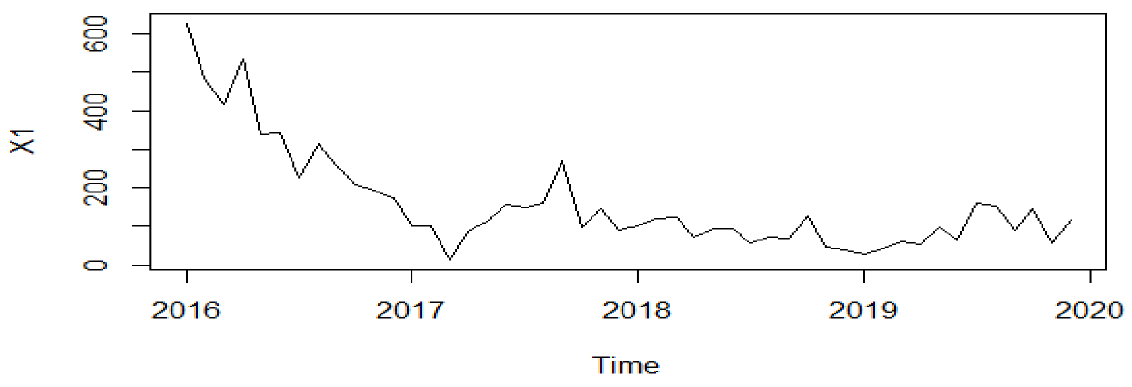


Figure 2: Malaria Cases recorded between 2016 to 2019

This time series helps display the total number of recorded malaria cases from 2016 to 2019 as presented in figure 2. The graph shows how the number of cases changes over time. The horizontal axis represents the years, and the vertical axis represents the total number of cases. Each point on the graph represents the number of cases recorded for a specific year. By looking at the graph, we can easily see any trends or patterns in malaria cases over the four years. It helps us understand how the number of cases fluctuates over time.

3.4 Estimating the Future Occurrence

Table 4: KPSS Test for Stationarity Check

	KPSS Test		
Series	**Test Statistics**	**P-Value**	**Remark**
Malaria	0.80994	0.01	**Stationary**

The hypothesis to be tested:

H_0: It has a unit root or the data is not stationary

H_1: It is a stationary data

Stationarity is determined by this probability, which is generated with *the* p-value (table 4). In general, the p-value is smaller than 0.05 indicating stationary data for malaria. Since the p-value of 0.01 is less than 0.05, we hereby reject the null hypothesis (Ho) and conclude that the cases of malaria are stationary y.

Table 5: Ljung-Box Test for Model Statistics

Model Statistics

Model	Number of Predictors	Model Fit Statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	

Malaria-Model	0	.626 .	12.424	15	.647	0

The hypothesis to be tested

H_o: The residuals are independently distributed

H_1: The residuals are dependently distributed, they exhibit serial correlation

The Ljung-Box test shows that with significant levels 0.647 (table 5), We accept the null (H_o) hypothesis since our p-values are greater than the given significance level (0.05), which signifies the values are auto-correlated and, the residuals for the time series model are independent for predicting the behavior of spread of malaria over some time.

Table 6: Fitting the ARIMA model for Malaria: six initial models

Malaria Models	**BIC conditions**	**Yes/no**
$(0,0,0)\ (0,0,0)_{12}$	11.43205	No
$(0,1,0)\ (0,0,0)_{12}$	12.47895	No
$(1,1,1)\ (0,0,0)_{12}$	11.35443	Yes
$(1,1,0)\ (0,0,0)_{12}$	11.77944	No
$(2,0,0)\ (0,0,0)_{12}$	11.35277	No
$(2,1,0)\ (0,0,0)_{12}$	11.61679	No

The values of pp and qq are then chosen by minimizing the BICs after differencing the data dd times (table 6). Rather than considering every possible combination of pp and qq, the algorithm uses a stepwise search to traverse the model space.

The best model (with the smallest BICs value) is set to be the “current model” for the diabetes model.

An ARIMA (1,1,1) model in figure 3 would have:

$p=1$p=1: One lag of the differenced series in the autoregressive part.

$d=1$d=1: First differencing to make the series stationary.

$q=1$q=1: One lag of the forecast errors in the moving average part.

The best model (with the smallest BICs value) is set to be the “current model” for the malaria model.

an ARIMA (0,1,1) model in figure 4 would have:

$p=0$p=0: No lag of the differenced series in the autoregressive part.

$d=1$d=1: One differencing to make the series stationary.

$q=1$q=1: One lag of the forecast errors in the moving average part.

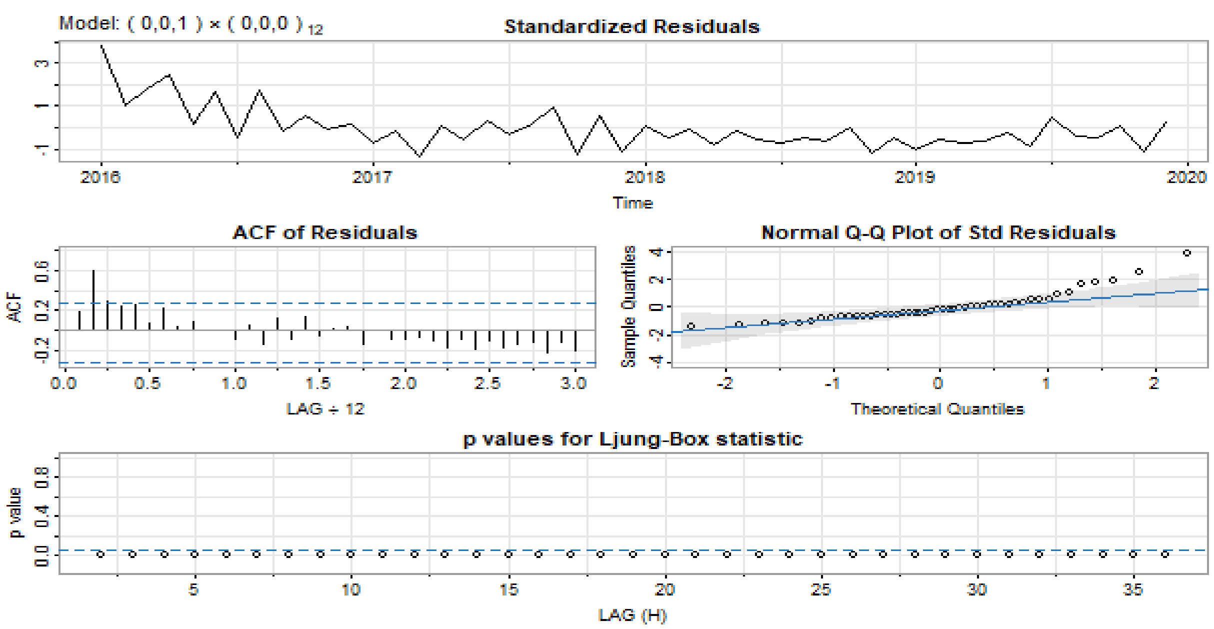


Figure 3: Standardized Residuals for the fitted model

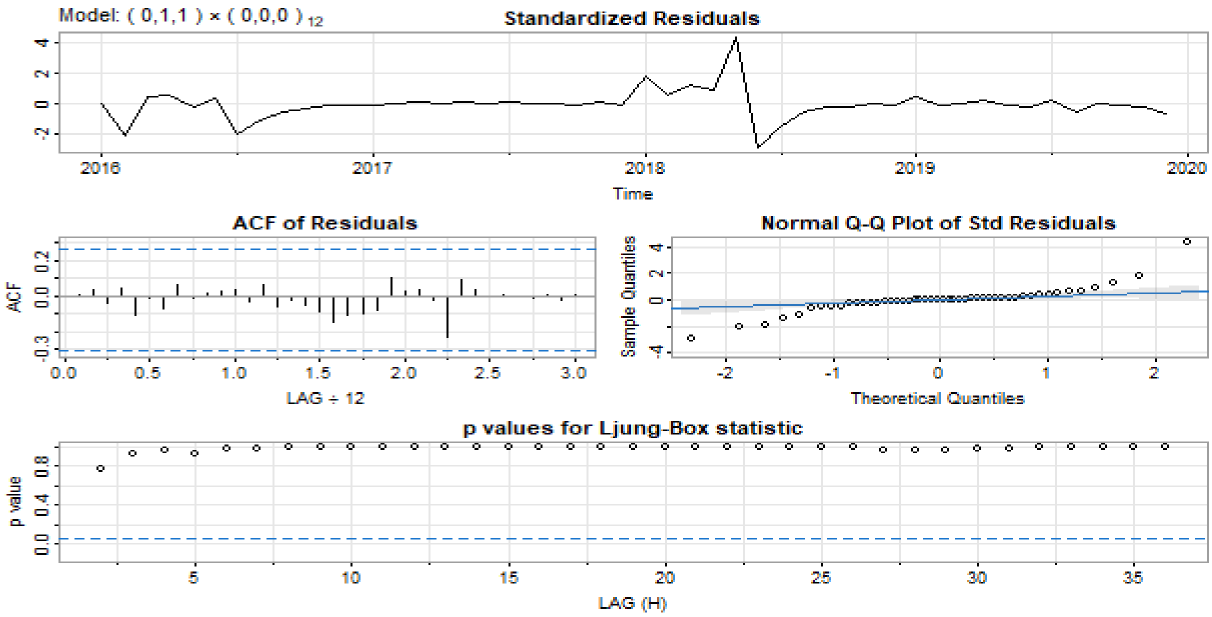
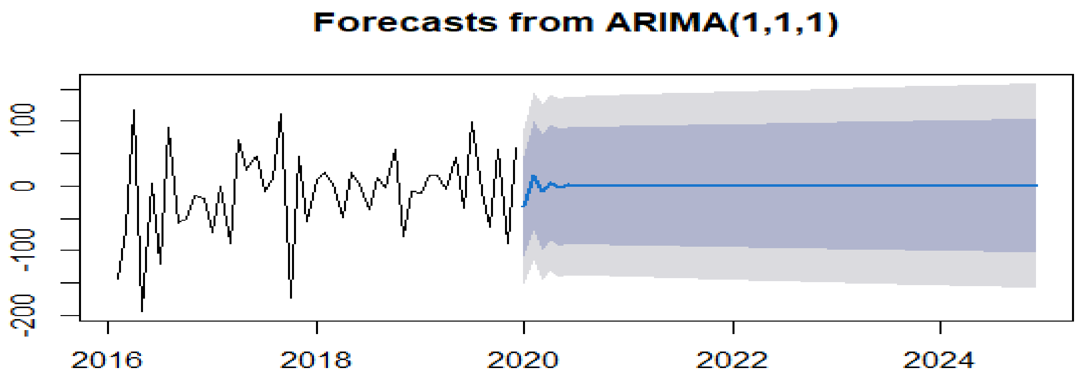


Figure 4: Standardized Residuals for the fitted model (0,1,1) (0,0,0)$_{12}$



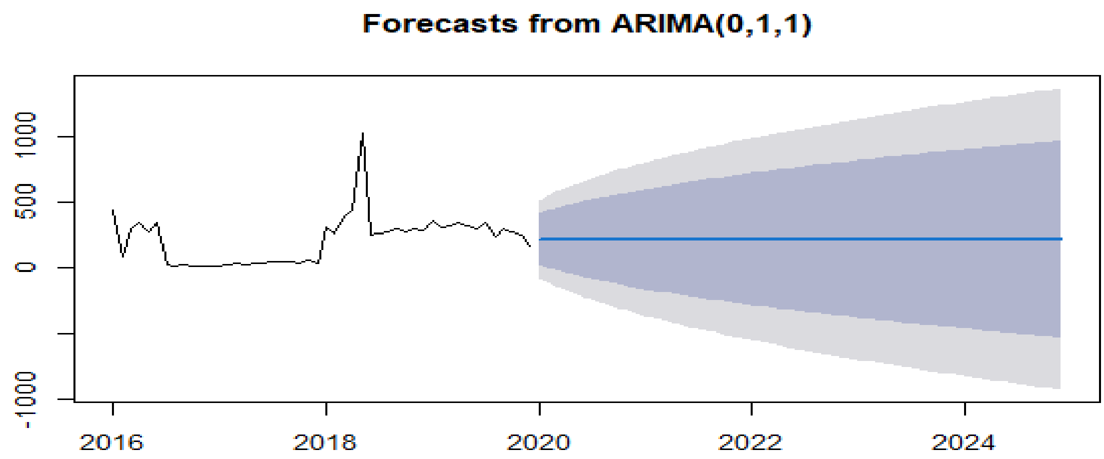


Figure 5: Predictive Analysis of the Incidence Cases of Malaria between 2020 to 2025

The predictive analysis of the incidence cases of malaria between 2020 to 2025 is shown in figure 5. This is a visual representation of the projected number of cases for both diseases during that period. It uses statistical models and historical data to make predictions about future trends. The graph has the years 2020 to 2025 on the horizontal axis and the predicted number of cases on the vertical axis. Each point on the graph would represent a specific year and show the estimated number of malaria and diabetes cases for that year. This type of graph helps us anticipate and understand the potential impact of these diseases in the coming years.

Table 7: Actual (2020) versus Predicted (2021) cases of Malaria

Month/Year	Actual Malaria Cases - 2019	Predicted Malaria Cases-2020
January	28	46.93716
February	44	101.39938
March	60	79.87718
April	55	93.72868
May	99	87.29308
June	64	91.28450
July	162	89.60448
August	154	90.91600
September	90	90.62248
October	147	91.18106
November	58	91.28347
December	117	91.62776
Total	**1078**	**1045.75523**

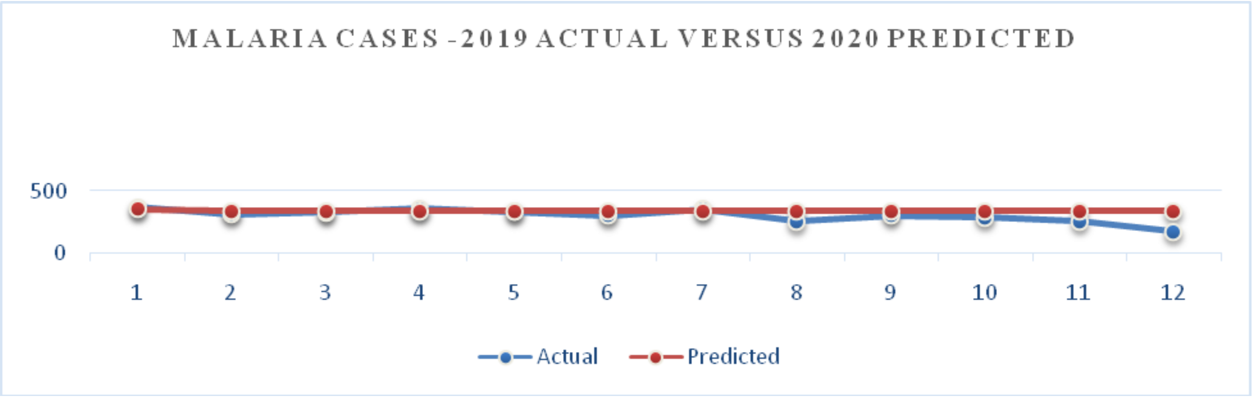


Figure 6: Malaria cases -2019 actual versus 2020 predicted

The graph that shows the actual number of malaria cases in 2019 (figure 6) compared to the predicted number of cases for 2020. This graph shows the difference between the real cases in 2019 and the estimated cases for 2020. The horizontal axis represents the years, with 2019 and 2020 being the specific years we're looking at. The vertical axis represents the number of malaria cases. The graph possesses two lines or bars, one showing the actual cases in 2019 and the other showing the predicted cases for 2020. By comparing these two, we can assess how accurate the predictions were and get an idea of the potential impact of malaria in 2020.

The actual data is 1078 and the predicted data is 1045 as revealed in table 7, which means that the number of malaria cases in 2020 was lower than what was initially predicted. This difference suggests that the situation may have been better than expected, with fewer cases occurring. It's always good news when the actual numbers turn out to be lower than actual statistics, as it means efforts to prevent and control malaria may have been effective.

3.5 Discussion

The chi-square test of association in this present study indicates a significant relationship between gender and disease occurrence, as evidenced by the p-value. This result suggests that the prevalence of the disease is influenced by gender, with one gender being more susceptible. This finding aligns with Singh et al. (2024), who reported a drop in annual malaria cases in India from 2.38 million (1990–2000) to 0.73 million (2011–2022), a 91% reduction from 1990 (2,018,783) to 2022 (176,522). Similarly, Howard et al. (2010) noted that most malaria studies in Nigeria have focused on recent infection trends or the effects of preventive measures. Generally, research on the correlation between environmental variables and malaria incidence has been conducted on smaller geographic scales (Tian et al., 2008; Huang et al., 2011).

In this current study, according to the correlation coefficient obtained -0.17, while the p-value is 0.254 which is greater than our p-value 0.05, Then the negative Correlation (-0.17) implies that there is a negative relationship between these two disease cases. We concluded and accepted the null hypothesis (H_o) and rejected our alternative hypothesis (H_1), saying there is no significant association between the disease cases involving malaria.. The total number of malaria cases expected in 2020 is approximately

1769, while the total number of diabetes expected in 2020 is 4131. The results of this study indicated an increase in the number of malaria cases over the period of forecast corroborating the study of Huang et al. (2011). A decrease was observed in the number of malaria cases between 2016 to 2019. A constant trend in diabetes cases is expected in the number of diabetes cases over the period of forecast. For the number of diabetes cases a significant increase was observed from 2017 to 2019.

The results of this study show that the incidence of malaria is affected or influenced by seasonal factors. Looking at the period under the study population (2016-2019), the highest and lowest occurrence of malaria cases were reported in January (858) and December (418) respectively while the highest and lowest occurrence of diabetes cases were reported in May (1675) and December (516). The identified models for period two for both malaria and diabetes were used to forecast future happenings taking into notice the seasonal factors and trends influencing the happenings of malaria and diabetes in the region. The forecast made in this study shows there will be an increase in the number of malaria cases expected around June to December 2020, which will be followed by a decrease with less occurrence around February to March and also May 2020 (Adegbite et al., 2023).

Analysis conducted in this paper complements these efforts by attempting to build a predictive tool that can be used to forecast malaria cases at a national level based on observations from a passive surveillance system that is currently in place. In a country such as Nigeria, where infrastructure is limited, a system that can accurately predict future malaria trends would be a great asset for public health planning and resource allocation as reported by Segun et al. (2020).

In addition, proposed model forecasts malaria as shown in this study revealed incidence based solely on passive surveillance data and widely available climate indices, enabling short-term predictions that may provide useful indicators of lapses in malaria control in a setting of ongoing civil unrest (Anokye et al., 2018). Not only were proposed models able to forecast malaria up to one year ahead with minimum data inputs, but they also provide a means to better understand malaria dynamics in a setting disproportionately affected by lack of resources, ongoing civil unrests, and climate change (Mendelsohn et al., 2006).

4.0 Conclusion

It is glaring from the historical data used in this research work and the results obtained that the incidence of malaria and diabetes are influenced by seasonal factors as the incidence of malaria and diabetes tends to be high at some periods and low at some other periods. A proper enlightenment program is recommended across genders to enlighten the people of the study population about the seasonal pattern and educate them on preventive measures, especially at the period when high incidence is expected. Glaring facts from the data show there is no correlation between the cases of malaria and diabetes. Further work is needed to determine the factors responsible for the obscene high and low incidence at different periods of the year in the study population, and more work should be done on enlightening people about these diseases and their effects.

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