

Forecasting Malaria Cases Among Pregnant Women in Rivers State Nigeria: A GARCH Time Series Analysis Modelling Using Reported Data

Lucky Wobodo Alerechi¹, Anthony Ike Wegbom^{2,3*}, Clement Kevin Edet³,
Emmanuel Oyinebifun Biu⁴

¹Department of Mathematics/Statistics, Ignatius Ajuru University of Education, Port Harcourt, Nigeria

²Department of Public Health Sciences, College of Medical Sciences, Rivers State University, Port Harcourt, Nigeria

³Department of Community Medicine, College of Medical Sciences, Rivers State University, Port Harcourt, Nigeria

⁴Department of Mathematics and Statistics, University of Port Harcourt, Port Harcourt, Nigeria

Email address:

wegbomanthony@gmail.com (Anthony Ike Wegbom)

*Corresponding author

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Abstract: Background: Malaria in pregnancy is considered a significant public health problem, for which over 25 million are at risk of the infection each year in sub-Saharan Africa including Nigeria. This is despite interventions and improvement in the diagnosis, and treatment techniques. This study, therefore, forecasted cases of malaria in pregnancy in Rivers State Nigeria in 2021 to 2024. Methods: The total number of reported malaria-in-pregnancy (MIP) cases from 2003 to 2020 was extracted from National Bureau of Statistics (NBS) database. Descriptive statistics was obtained for the series plots, monthly mean plot, and yearly mean plot. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was used to forecast the monthly number of MIP for 2021 to 2024. Results: The time series plot showed that there was a high volatility in the year 2020 in the malaria data. Also, the result shown that GARCH (0,1) and GARCH (1,1) parameters were all significant at 5% significance level. GARCH (1,1) model have least AIC value and log likelihood ratio among the several models. The study revealed an increasing trend in the number of MIP from 2021 to 2024. Conclusion: The study showed an expected increase for the forecasted period. The forecasted malaria cases will help Government and its health agencies, and critical stakeholders to plan and implement interventions to prevent the disease and mitigate its negative effects on mothers and fetus.

Keywords: Malaria in Pregnancy, Generalized Autoregressive Conditional Heteroskedasticity Model, Akaike Information Criterion (AIC), Forecasts

1. Introduction

Malaria is a parasitic disease that infects humans and is spread by female *Anopheles* mosquitoes [1]. Globally, there has been decline in the reported cases of malaria and associated death. From 233 million reported cases and 985,000 deaths in 2000 to about 229 million cases and 409,000 deaths in 2019 [2, 3], but it remained the commonest tropical disease with high fatality, and negative economic and social impacts [4]. Sub-Saharan Africa is considered home to

over 90% of all malaria-related deaths, and nearly 85% of all deaths worldwide [3, 5].

Approximately 50 percent of the Nigerian population suffers at least one incidence of malaria every year especially in rural villages occasioned by lack of or inadequate medical diagnoses or treatment facilities [6]. The largest global malaria cases and deaths (27% and 23% respectively) were reported in Nigeria in 2019, which resulted to 3.5% increase in the number of cases from 293 to 303 per 1000 of the population at risk between 2016 and 2019 and decline in the

number of deaths by 16% from 0.57 to 0.47 per 1000 of the population at risk during the period under review [7]. Similarly, the 2018 Nigeria Demographic and Health Survey (NDHS) revealed 23% prevalence of malaria in under-five children, with rural-urban, regional, and socioeconomic inequalities [8].

Malaria is considered a significant public health problem, particularly during pregnancy in sub-Saharan Africa where over 25 million were at risk of the infection each year [9]. This is despite improvement in the diagnosis, prevention, and treatment techniques [1]. Studies conducted in different parts of Nigeria showed the prevalence of malaria in pregnancy as 40.2% in the south [10] and 55.0% in the north [11]. Another study in Ethiopia [9] showed that 10.2% pregnant women were infected with malaria infection.

Pregnant women were at increased risk due to the immunological depression [12], although, it might be asymptomatic for women residing in high endemic areas due to their acquired immunity [9]. Malaria in pregnancy (MIP) adversely affect the mother, fetus and neonates [9, 13]. *Plasmodium falciparum*, the most prevalent malaria species in Africa, is mostly to blame for the burden of malaria infection during pregnancy [8, 9], and causes maternal anaemia, prenatal mortality, and low birth weight [14].

Rivers State is one of the states in Nigeria, where malaria is endemic, and people are at a high risk for being infected. Despite the burden of malaria in the state, there is limited evidence on the magnitude and trend of malaria infection among pregnant women for the planning of interventions to mitigate its adverse effect on mother, fetus and neonates by the relevant authorities, and accelerate the Sustainable Development Goals (SDGs) on maternal health. This study, therefore, forecasted malaria in pregnancy from 2021 to 2024 using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Time Series analysis model approach.

2. Methods

2.1. Research Design

The descriptive research design was adopted for the study to determine the trends of malaria in pregnancy and forecast the volatility of the data.

2.2. Study Area

Rivers State is situated in south-south region of Nigeria in which the inland area is comprised of tropical rainforest towards the coast. The state was formed out of the Eastern region in 1967 with its capital in Port Harcourt. Rivers State is split into twenty-three local government areas, grouped under three senatorial districts zones. It has borders with

(south) Atlantic Ocean, (north) Anambra, Imo, and Abia States, (East) Akwa Ibom State, (West) Bayelsa and Delta States. The state capital, Port Harcourt, is a metropolis that is considered the commercial center of the Nigerian oil industry. Rivers State is the 6th most populous state in Nigeria, with a population of 5,198,716 and extrapolate at 3.4 growth rate per year as at the 2006 census. Rivers State is a diverse state that is home to many minorities' ethnic groups, including the Ogoni, Ikwerre, Ijaw, and Okrika people.

2.3. Data Source

The data was extracted from National Bureau of Statistics (NBS) annual statistical report from year 2003 to 2020 for malaria cases in pregnant women in Rivers State.

2.4. Method of Data Analysis

The collected data were analysed using Gretl statistical software to forecast the volatility of the dataset using Generalised Autoregressive Conditional Heteroskedasticity (GARCH).

The GARCH proposed by Bollerslev [15] in 1986 is expressed as.

$$\sigma_t^2 = \beta_0 + \sum_{n=1}^q \beta_n \varepsilon_{t-n}^2 + \sum_{m=1}^p \beta_m \sigma_{t-m}^2 \quad (1)$$

The assumptions $\beta_0 > 0$, $\beta_n \geq 0$ and $\beta_m \geq 0$; $n = 1, 2, \dots, q$ and $m = 1, 2, \dots, p$ is required to ensure the firm positivity of the conditional variance or volatility σ_t^2 . Stationarity of the GARCH model occurs when $\beta_n + \beta_m < 1$, as $\beta_n + \beta_m$ gets close to 1 the volatility becomes more persistent. If $\beta_n + \beta_m \geq 1$, a new form of GARCH model occurs called Integrated GARCH or IGARCH.

Model selection or good fit was based on Akaike Information Criterion (AIC) value, the model with lowest AIC value the better. It is expressed as:

$$AIC = 2k - 2\ln(L) \quad (2)$$

where,

K= number of explanatory parameters.

L= Maximized value of the likelihood function for the estimated model (the likelihood that the model could have produced your observed independent (y)-values).

3. Results

The data used in this work were secondary data obtained from National Bureau of Statistics (NBS) website- (<https://www.nigerianstat.gov.ng>) which consist of monthly malaria cases in pregnant women in Rivers State data from 2003-2020, where we have total observations of 216.

Table 1. Descriptive Statistics result.

Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Minimum	Maximum
7498	417	6284	4962	6132	37595335	1.906329	1.365953	417	26343

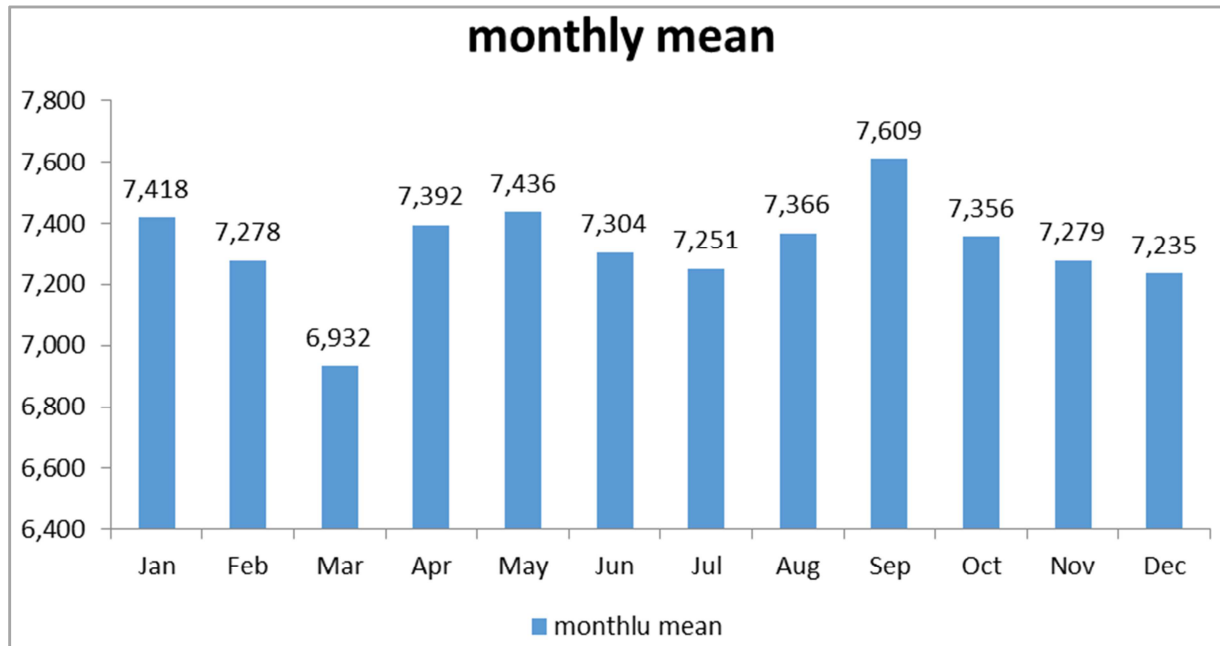


Figure 1. Bar Chart Result of Monthly Mean Plot of the Reported Cases of Malaria.

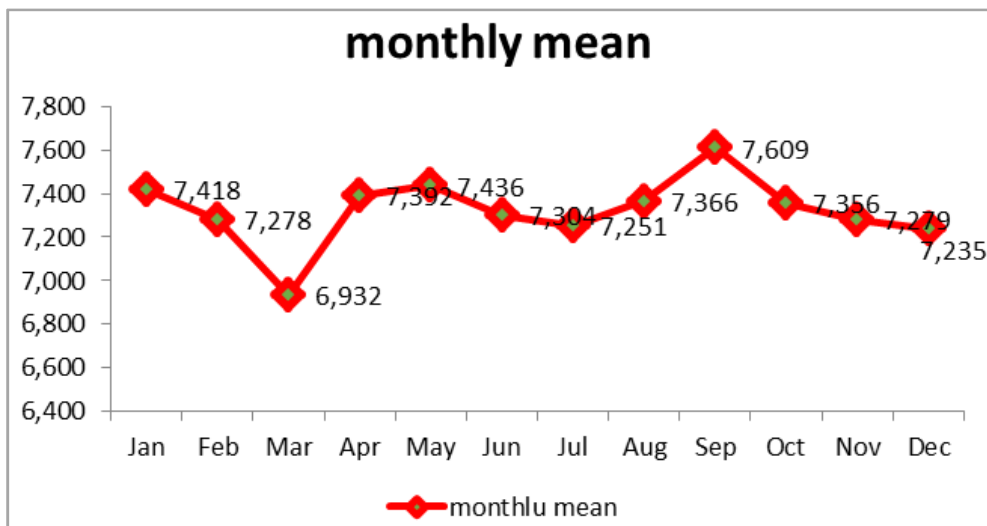


Figure 2. Line Plot of Monthly Mean of the Reported Cases of Malaria.

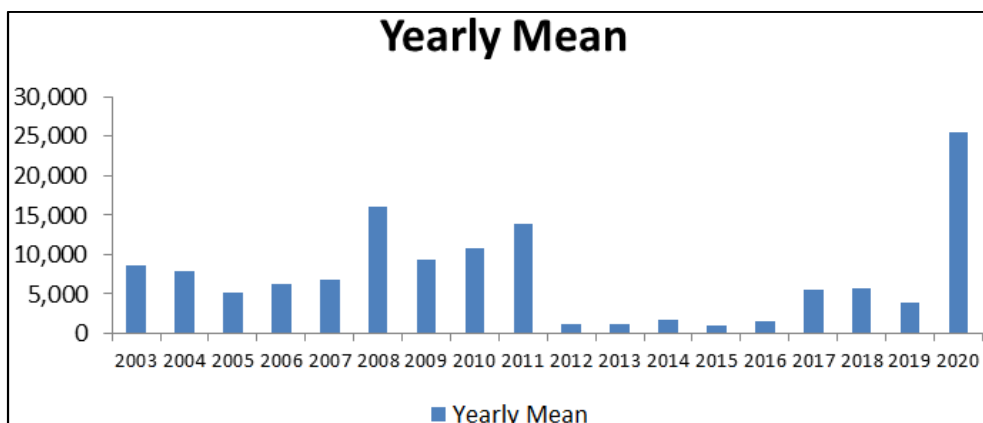


Figure 3. Bar Chart Plot of Yearly Mean of the Reported Cases of Malaria.

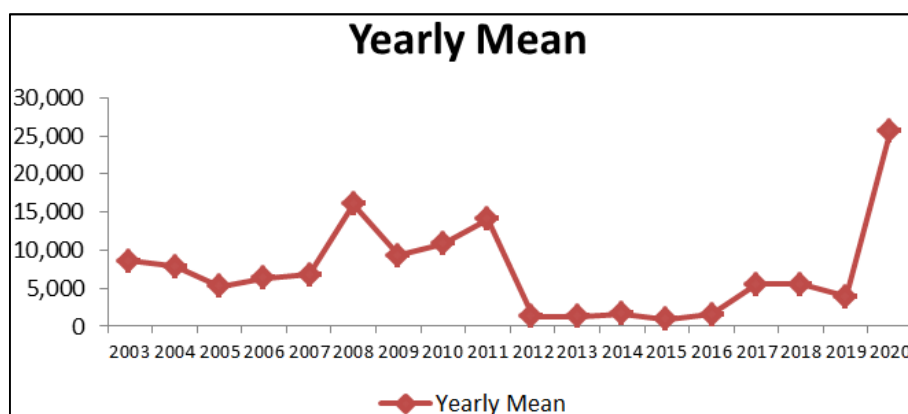


Figure 4. Line Plot of Yearly Mean of the Reported Cases of Malaria in Pregnant women.

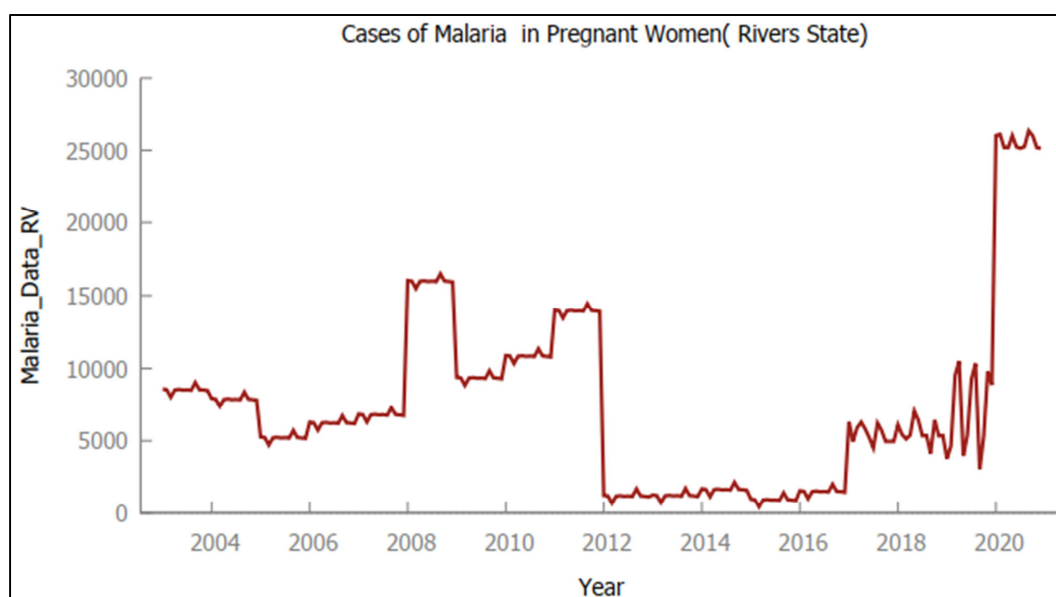


Figure 5. Rivers State Malaria Cases in Pregnant Women Series.

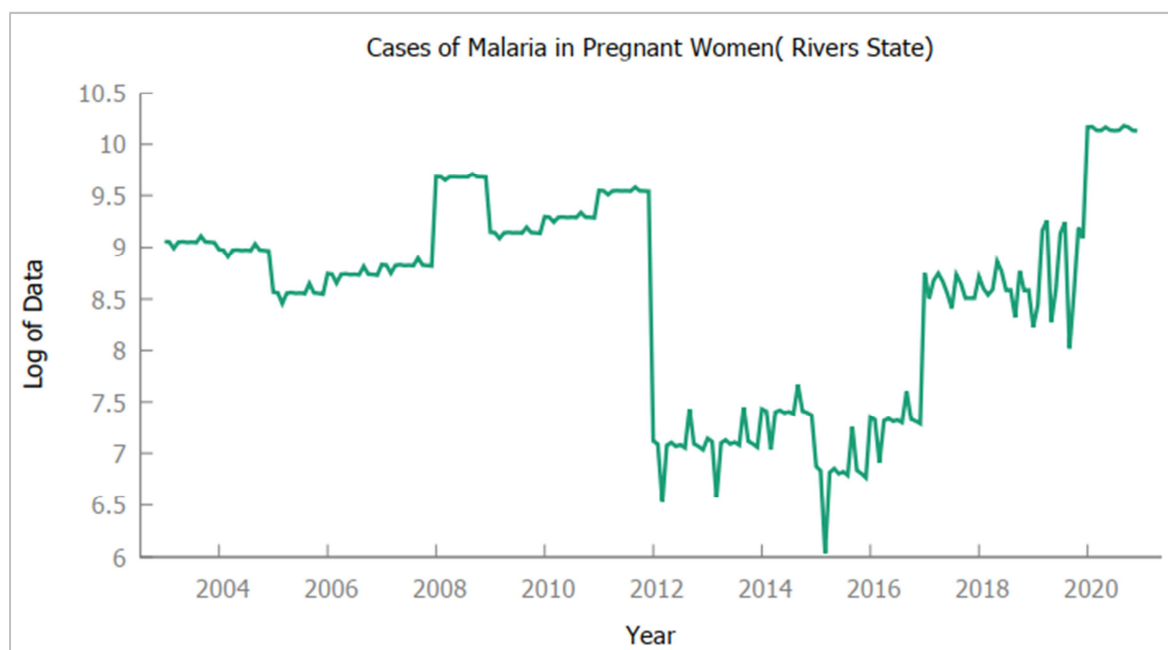


Figure 6. Log Transformation of Rivers State Malaria Cases in Pregnant Women Series.

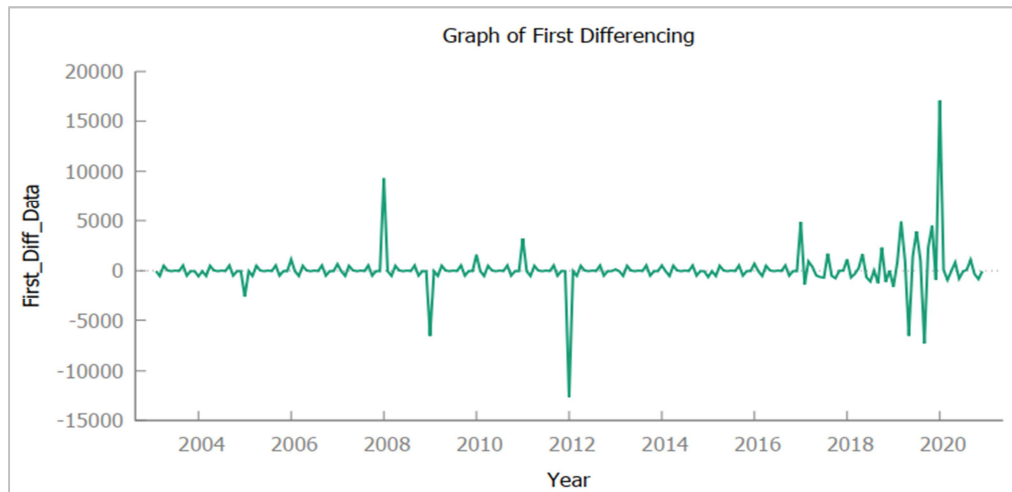


Figure 7. Differencing of Actual data (Malaria in Pregnant Women).

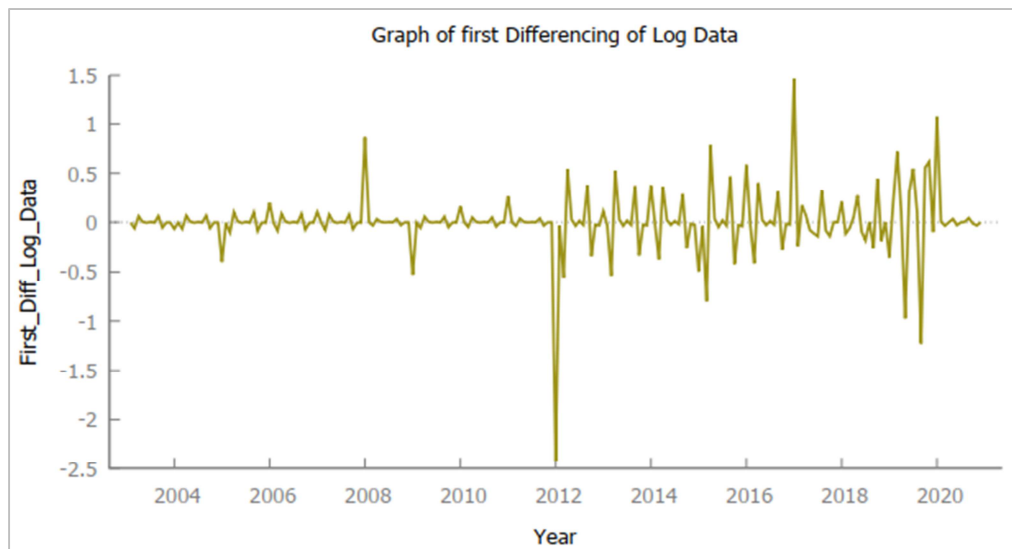


Figure 8. Differencing of Log data (Malaria in Pregnant Women).

Table 2. Malaria in Pregnant Women Estimated GARCH Models with Constant and their Parameters.

Variable	Model	Parameter Estimates (Coefficients & P-values)	AIC	Log-Likelihood	Remark
Actual Data	GARCH (0, 1)	$\theta = 5810.37$ (6.65e-185) *	4688.231	-2090.116	GARCH (0,1)
	GARCH (1, 0)	$\alpha_1 = 1.0000$ (2.65e-014) *	-	-	
	GARCH (1, 1)	-	-	-	
Log of Data	GARCH (0, 1)	$\theta = 8.77603$ (0.0000) *	388.771	-190.385	GARCH (0,1)
	GARCH (1, 0)	$\alpha_1 = 0.9937$ (3.38e-015) *	-	-	
	GARCH (1, 1)	$\theta = 8.77398$ (0.0000) *	390.057	-190.0285	
First Differencing of Data	GARCH (1, 1)	$\alpha_1 = 0.95826$ (1.55e-01) *	-	-	GARCH (1, 1)
	GARCH (0, 1)	$\beta_1 = 0.035736$ (0.6480)	-	-	
	GARCH (1, 0)	-	-	-	
First Differencing of Log Data	GARCH (1, 1)	$\theta = 24.0411$ (0.8326)	3846.046	-1918.023	GARCH (1, 1)
	GARCH (0, 1)	$\alpha_1 = 0.30272$ (0.0615) *	-	-	
	GARCH (1, 0)	$\beta_1 = 0.52903$ (1.51e-05) *	-	-	
First Differencing of Log Data	GARCH (1, 1)	$\theta = 0.0022286$ (0.9132)	112.883	-51.441	GARCH (1, 1)
	GARCH (0, 1)	$\alpha_1 = 0.056095$ (0.2455) *	-	-	
	GARCH (1, 0)	$\beta_1 = 0.597928$ (0.0011) *	-	-	

*Significance at 5% level of significance.

Table 3. Malaria in Pregnant Women Estimated GARCH Models without Constant and their Parameters.

Variable	Model	Parameter Estimates (Coefficients & P-values)	AIC	Log-Likelihood	Remark
Actual Data	GARCH (0, 1)	$\alpha_1 = 1.0000 (1.14e-021) *$	4356.994	-2170.50	GARCH (1, 1)
	GARCH (1, 0)	-	-	-	
	GARCH (1, 1)	$\alpha_1 = 0.9987 (3.28e-019) *$ $\beta_1 = 0.00135 (0.9683)$	4348.994	-2170.497	
Log of Data	GARCH (0, 1)	$\alpha_1 = 0.95189 (0.0153) *$	1542.793	-768.396	GARCH (0, 1)
	GARCH (1, 0)	-	-	-	
	GARCH (1, 1)	$\alpha_1 = 0.79951 (0.5304)$ $\beta_1 = 0.17147 (0.8991)$	1544.776	-768.388	
First Differencing of Data	GARCH (0, 1)	-	-	-	GARCH (1, 1)
	GARCH (1, 0)	-	-	-	
	GARCH (1, 1)	$\alpha_1 = 0.30001 (0.0605) *$ $\beta_1 = 0.53003 (1.53e-05) *$	3844.09	-1918.045	
First Differencing of Log Data	GARCH (0, 1)	-	-	-	GARCH (1, 1)
	GARCH (1, 0)	-	-	-	
	GARCH (1, 1)	$\alpha_1 = 0.056371 (0.2433)$ $\beta_1 = 0.597669 (0.0011) *$	110.895	-51.447	

*Significance at 5% level of significance.

The figures 1 and 2 show that on the average Rivers State recorded the highest cases of malaria in the month of September cumulatively (7,609).

The Figures 3 and 4 show the in the year 2020 Rivers State had the highest malaria cases in pregnant women, this maybe because of the Covid 19 pandemic.

The Plots of the actual data, Log transformation of the data set, first differencing of the log transformation and the actual data difference are shown below, figures 5 to 8.

Figure 5 shows an upward trend from January 2004 to 2012, then a downward drop from the year 2012 to 2019 while from 2019 to 2020, a sharp growth was observed in the series. This could be due to increase rain fall and flood associated with climate change, and the effect of covid-19 outbreak in Nigeria and the World at large.

Figure 6 shows clearly the behaviour of the data set in Figure 5 after log transformation was applied. The transformed series shows that the variance is stabilized.

Figures 7 and 8 show that data are stationary with evident of volatility in the two different series. Therefore, suitable GARCH model will be appropriate in predicting Rivers

State malaria cases. Several GARCH models were built to identify a suitable model for predicting malaria case in River State. The model estimation and parameter estimates, AIC and Likelihood ratios are summarized in Table 3 and Table 4.

By comparing the several GARCH models in Table 2 we noticed that GARCH (0,1) model has the highest absolute log likelihood ratio value of 2090.50. Hence, from the result of GARCH models with constants in Table 2, GARCH (0,1) model is identified as the best model. Also, all the parameters of GARCH (0,1) models were significant at 5%.

Similarly in Table 3, comparing the GARCH models without constants, we noticed that GARCH (0,1) and GARCH (1,1) parameters were all significant at 5% and had the same absolute log likelihood ratio value 2170.50 but with different AIC values of 4356.994 and 4348.994 respectively. GARCH (1,1) was chosen as the best model because it has a lower AIC value when compared with GARCH (0,1) model.

Recall that the general form of a GARCH (p, q) model equation in which there are p lagged terms of the lagged conditional variances and q terms of the squared error term is

$$\sigma_t^2 = \theta + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \dots + \beta_p \sigma_{t-p}^2 \quad (3)$$

The mathematical expressions for the best GARCH models identified above with constant and the one without constant are stated below in equations (4) and (5) respectively-

$$\text{GARCH (0,1): } \sigma_t^2 = \theta + \alpha_1 \varepsilon_{t-1}^2 \quad (4)$$

$$\text{GARCH (1,1): } \sigma_t^2 = \theta + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (5)$$

Substituting the values of the parameter estimates in Tables 2 and 3 into equations (4) and (5) we have-
GARCH (0,1):

$$\sigma_t^2 = 5810.37 + 1.0000 \varepsilon_{t-1}^2 \quad (6)$$

GARCH (1,1):

$$\sigma_t^2 = 0.00233 + 0.05610 \varepsilon_{t-1}^2 + 0.59793 \sigma_{t-1}^2 \quad (7)$$

From the two models, GARCH (1,1) model was identified as the best model in terms of having a minimum AIC value. Hence, the identified adequate GARCH (1,1) model used to make a forecast for the year 2021-2024.

Forecasts for 2021 and 2024 with 95% Confidence Interval (C. I).

$$\hat{\sigma}_{t(216)}^2 = 0.00233 + 0.05610\varepsilon_{t(215)}^2 + 0.59793\sigma_{t(215)}^2 \quad (8)$$

Table 4. Malaria in Pregnant women Forecasts for year 2021 and 2024.

Year	Month	Malaria in Pregnant women Forecasts	Lower 95%	Upper 95%
2021	Jan	26,591	19,927	34,924
	Feb	26,632	19,968	34,965
	Mar	28,086	21,422	36,419
	Apr	28,209	21,545	36,542
	May	29,669	23,005	38,002
	Jun	29,874	23,210	38,207
	Jul	31,345	24,681	39,678
	Aug	31,633	24,969	39,966
	Sep	33,120	26,456	41,453
	Oct	33,491	26,827	41,824
	Nov	35,000	28,336	43,333
	Dec	35,455	28,791	43,788
2022	Jan	36,990	30,326	45,323
	Feb	37,531	30,867	45,864
	Mar	39,096	32,432	47,429
	Apr	39,725	33,061	48,058
	May	41,325	34,661	49,658
	Jun	42,044	35,380	50,377
	Jul	43,684	37,020	52,017
	Aug	44,495	37,831	52,828
	Sep	46,181	39,517	54,514
	Oct	47,087	40,423	55,420
	Nov	48,823	42,159	57,156
	Dec	49,826	43,162	58,159
2023	Jan	51,619	44,955	59,952
	Feb	52,723	46,059	61,056
	Mar	54,577	47,913	62,910
	Apr	55,785	49,121	64,118
	May	57,707	51,043	66,040
	Jun	59,023	52,359	67,356
	Jul	61,019	54,355	69,352
	Aug	62,447	55,783	70,780
	Sep	64,523	57,859	72,856
	Oct	66,067	59,403	74,400
	Nov	68,230	61,566	76,563
	Dec	69,895	63,231	78,228
2024	Jan	72,152	65,488	80,485
	Feb	73,944	67,280	82,277
	Mar	76,300	69,636	84,633
	Apr	78,225	71,561	86,558
	May	80,689	74,025	89,022
	Jun	82,752	76,088	91,085
	Jul	85,332	78,668	93,665
	Aug	87,540	80,876	95,873
	Sep	90,244	83,580	98,577
	Oct	92,603	85,939	100,936
	Nov	95,440	88,776	103,773
	Dec	97,958	91,294	106,291

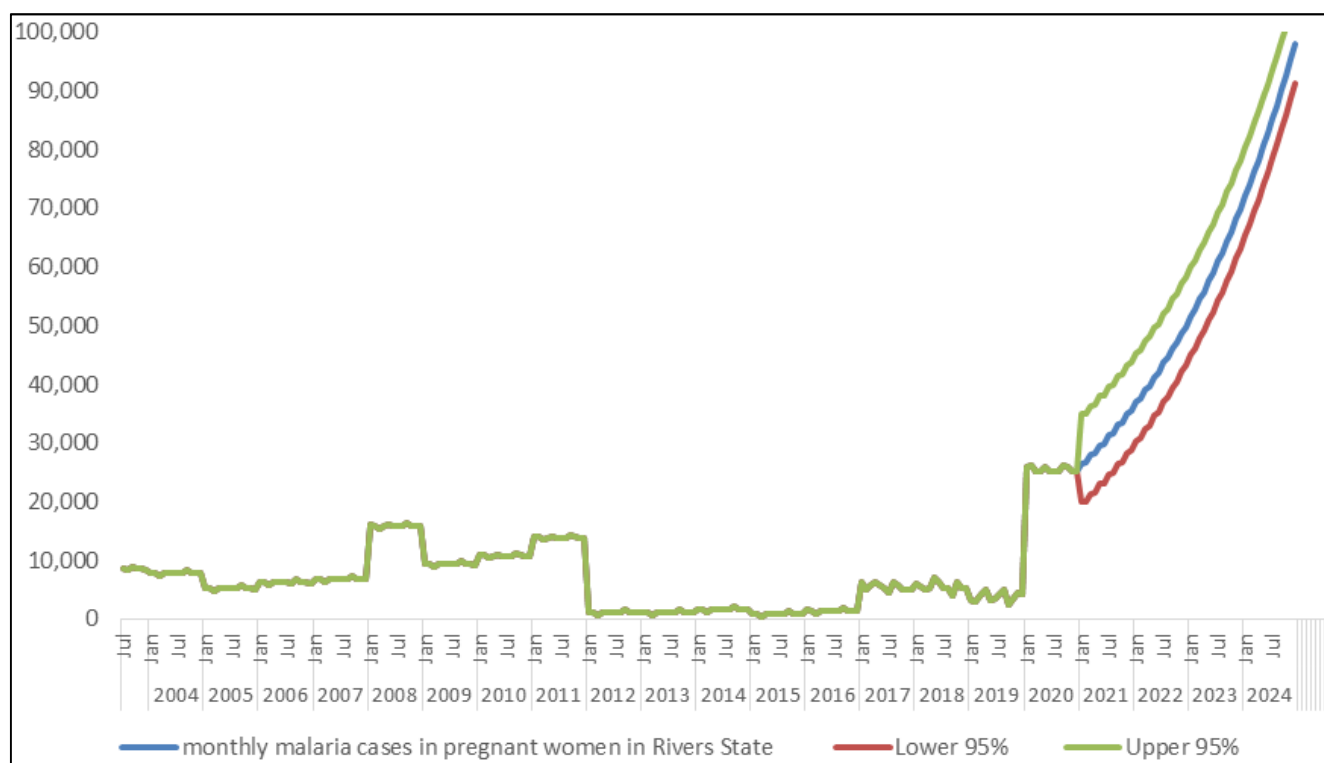


Figure 9. Expected Cases of Malaria in Pregnant women, Rivers State for year 2021 and 2024 (Forecasts).

This predict suitable forecast values trend should be giving attention by Government and health organizations in Figure 9.

4. Discussion

The burden of malaria infection during pregnancy is caused mainly by *Plasmodium falciparum*, the most common malaria species in Africa [8]. Each year at least 3 million pregnancies occur among women in malarious areas of Africa, most of who reside in areas of relatively stable malaria transmission [3]. Pregnant women and the unborn children are particularly vulnerable to malaria, which is a major cause of prenatal mortality, low birth weight, and maternal anaemia [10]. Therefore, in this study, the estimation of the descriptive statistics of malaria cases in pregnant women in Rivers State was done; obtaining the series plots, identification of a suitable model for forecasting of was also done using a GARCH model. Then prediction for the years 2021 and 2024, which is showing an upward trend of expected cases of Malaria in Pregnant women in Rivers State. The result is like previous study conducted in Northern Nigeria [6].

The limitation of this study was based on the use of reported data. Like most secondary data, it is always associated with misreporting and underreporting. The forecast values could also be distorted by the current government interventions on malaria such as the roll back malaria programme, as interventions was not factor in the model. Nevertheless, the study provides evidence of malaria trends among pregnant women in Rivers State Nigeria.

5. Conclusion

This study used reported data with GARCH model to predict the average monthly malaria cases among pregnant women in Rivers State. The results showed an expected increase for the forecasted period. We therefore recommend that Government and health agencies, and critical stakeholders should plan and implement interventions to prevent the disease and mitigate its negative effects on mothers and fetus. This will accelerate the drive to achieve the Sustainable Development Goals relating to maternal and child health.

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