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RBM-Programme Impact Evaluation: An Interrupted Time Series Analysis

Elisha J. Inyang
Department of Statistics
University of Uyo

Pradeep Mishra
College of Agriculture, Rewa, Jawaharlal Nehru Krishi Vishwavidyalaya, Jabalpur, India

Kingdom Nwuju
Department of Mathematics
Rivers State University, Nigeria

Godwin Udo
University of Texas at El Paso
El Paso, USA

ABSTRACT

This study employs the Box-Tiao time series modeling approach to assess the impact of the Roll Back Malaria initiative on childhood malaria incidence in a state in Nigeria. Childhood diseases, particularly malaria, significantly contribute to morbidity and mortality in developing countries, with malaria being the leading cause of death among African children. The RBM programme, launched in 1998, aimed to reduce malaria-related mortality by 50% by 2010. An exploratory data analysis revealed a mean incidence rate of 277.69, with significant variability and a right-skewed distribution, highlighting higher incidence cases. This necessitates targeted public health interventions to address these outliers effectively. The intervention model using an ARIMA noise component indicates a substantial decrease in malaria incidence following the RBM intervention, with a rapid return to pre-intervention levels and a delayed intervention effect. The results underscore the importance of sustained public health efforts and adequate funding to combat malaria effectively. This study contributes to understanding malaria dynamics and the efficacy of intervention strategies, offering valuable insights for policymakers in the fight against childhood malaria.

Keywords: Roll Back Malaria, Time series, Box-Tiao approach, Childhood malaria, Evaluation

1. Introduction

Childhood diseases are significant contributors to morbidity and mortality in children, particularly in developing countries. Mortality rates serve as critical indicators of population dynamics, disproportionately affecting infants and the elderly. Diseases such as malaria, upper respiratory tract infections, measles, anemia, chickenpox, pneumonia, tetanus, and polio predominantly impact children aged zero to fourteen years. The heightened susceptibility of children to various illnesses is often linked to their frequent exposure to pathogens and environmental risks. Alarmingly, preventable childhood diseases claim the lives of over one million Nigerian children annually, especially those under five years of age, [38]. Among these, malaria, diarrhea, pneumonia, measles, malnutrition, and HIV/AIDS stand out as the leading causes of childhood mortality in developing regions.

Across malaria endemic regions, the disease affects all age groups, but it is especially devastating in Africa, where it is the leading cause of death among young children. The disease claims the life of a child every 30 seconds worldwide, primarily by destroying red blood cells and leading to complications such as anemia and respiratory infections. In response to the substantial public health burden posed by malaria, the Roll Back Malaria (RBM) initiative was established in

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- Elisha J. Inyang (corresponding author) is affiliated with Department of Statistics, University of Uyo.
  inyang.elisha@yahoo.com

1998 as a joint effort among the World Health Organization (WHO), the World Bank, the United Nations Development Programme (UNDP), and the United Nations International Children's Emergency Fund (UNICEF). The initiative set an ambitious target of reducing malaria-related mortality by 50 percent by the year 2010, a commitment that received formal endorsement from African heads of state at the Abuja Summit held in Nigeria in 2000 [41-42]. This initiative's endorsement was particularly significant given that nearly 90 percent of the estimated 1,000,000 malaria-related deaths each year occur in Africa, with children and pregnant women disproportionately affected [39].

The Roll Back Malaria (RBM) partnership established a structured governance framework in 2003, which included subregional networks, country partnership advisors, prominent advocates, and specialized working groups tasked with developing and disseminating best practices for the expansion of malaria control interventions. To support these activities, a central secretariat was established at the World Health Organization headquarters in Geneva, Switzerland, where it coordinated partner contributions to ensure alignment with country specific priorities and evidence based recommendations [36, 40]. Primary interventions aimed at reducing malaria associated mortality include the widespread deployment of insecticide treated bed nets, the administration of artemisinin-based combination therapies, and the application of indoor residual spraying. Comprehensive malaria control is grounded in several core components: preventive strategies focused largely on vector management; rapid detection and response to malaria outbreaks; targeted protection of pregnant women through measures such as intermittent preventive treatment; and the timely provision of effective therapy for all confirmed malaria infections [39].

Notwithstanding sustained international initiatives, financial resources allocated to malaria control continue to fall short of required levels. It has been estimated that approximately US$1 billion per year is necessary to provide artemisinin-based combination therapies to roughly sixty percent of affected populations; however, total global assistance for malaria control was reported to be only about US$100 million in the year 2000, as noted by Narasimhan and Attaran [29]. However, annual funding has increased due to initiatives like the Global Fund, which disbursed $37.3 million to malaria programs by October 2003. Yet, this amount remains insufficient given the scale of the crisis. As of 2021, the World Health Organization reported 247 million malaria cases globally, resulting in approximately 619,000 deaths, with 77% of these fatalities occurring in children under five years of age—an alarming daily toll exceeding one thousand young lives, [37]. Addressing these challenges requires sustained commitment, increased funding, and innovative strategies to combat childhood diseases effectively.

A critical understanding of malaria must be underpinned by statistical and mathematical models in order to develop intervention programs rationally. Time Series techniques are very significant for forecasting and discovering the mechanism that generates the dataset. The well-known time series model is the ARIMA model. In literature, many authors have predicted malaria incidence using the ARIMA models to predict malaria surveillance (Anokye *et al.* [3], Anwar *et al.* [4], Musa [28], Adeyeye and Nkemnole [1], Riaz *et al.* [32]).

However, the predictive performance of the ARIMA framework can be compromised when the time series is disrupted by exogenous events (Etuk *et al.* [12]; Inyang *et al*. [15-21]). However, this can be improved by employing the intervention analysis technique (Box and Tiao [8], Darkwah *et al.* [10], Girard [13], Inyang [14], Inyang *et al.* [15-20], Jarrett and Kyper [22], Lai and Lu [23], Min [25], Moffat and Inyang [26], Nelson [30], Sharma and Khare [34], Shittu and Inyang [35]). Therefore, this study employed the Box-Tiao time series modeling approach to investigate the

impact of the Roll Back Malaria intervention and also to discover the process's generating mechanism by fitting an appropriate model for the studied series.

2. Methodology

2.1 Data Description

The study's data set consists of monthly childhood malaria incidence from January 1997 to December 2011, which were gathered from records of five chosen from the state's three senatorial districts. The dataset was divided into observations belonging to pre-intervention (January 1997 to September 2003) and post-intervention periods (October 2003 to December 2011). All statistical analyses in this study were conducted using the R Programming Language (Version 4.1.3 for Windows) [31].

2.2 Model Specification

2.2.1 Autoregressive Integrated Moving Average Process

The autoregressive integrated moving average process is an integrated series that is composed of the autoregressive and the moving average process [5-7]. Given an ARMA model with parameters $ARMA(p,q)$ and the differencing order, $\mathcal{L}$, the resulting model is denoted by $ARIMA(p,\mathcal{L},q)$, written using the backward shift operator as:

$$\mathcal{S}(\delta)\,\nabla^{\mathcal{L}}\mathcal{H}_t = \mathcal{V}(\delta)\beth_t \quad (1)$$

With a backward shift operator δ defined as:

$$\delta^k\mathcal{H}_t = \mathcal{H}_{t-k}, \delta^0 \equiv 1\,, \delta\mathcal{H}_t = \mathcal{H}_{t-1} \quad (2)$$

$$\mathcal{S}(\,\delta) = 1 - \mathcal{S}_1\,\delta - \mathcal{S}_2\,\delta^2 - \cdots - \mathcal{S}_p\,\delta^p \quad (3)$$

$$\mathcal{V}(\,\delta) = 1 + \mathcal{V}_1\,\delta + \mathcal{V}_2\,\delta^2 + \cdots + \mathcal{V}_q\,\delta^q \quad (4)$$

$$\nabla^{\mathcal{L}}\mathcal{H}_t = \nabla(\nabla^{\mathcal{L}-1}\mathcal{H}_t) = (1 - \delta)^{\mathcal{L}}\mathcal{H}_t \quad (5)$$

Where;

$\mathcal{H}_t$ is the childhood malaria incidence at time t; $\mathcal{S}'s$ and $\mathcal{V}'s$ are the autoregressive and moving average parameters; $\mathcal{L}$ is the order of differencing; δ backward shift operator; $\beth_t$ is the error term.

2.2.2 ARIMA-Intervention

The most popular method for modelling and forecasting has been identified as the Box-Jenkins ARIMA model. However, the ARIMA model's ability to forecast may be compromised when outside events have an impact on the time series. Consequently, the ARIMA-Intervention analysis proposed by [8] is recommended, defined as:

$$\mathcal{H}_t = \frac{\mathcal{A}(\delta)}{\mathcal{Z}(\delta)}\mathcal{F}_{t-\lambda} + \frac{\mathcal{V}(\,\delta)}{\mathcal{S}(\,\delta)}\beth_t \quad (6)$$

(6) can be reduced to:

$$\mathcal{H}_t = \mathfrak{F}(\delta) + \Re_t \quad (7)$$

$\mathfrak{F}(\delta)$ and $\mathfrak{R}_t$ are respectively the transfer function and noise component of the intervention model, represented by;

$$\mathfrak{F}(\delta) = \frac{\mathcal{A}(\delta)}{\mathcal{Z}(\delta)}\mathcal{F}_{t-\lambda} \text{ and } \mathfrak{R}_t = \frac{\mathcal{V}(\delta)}{\mathcal{S}(\delta)}\mathfrak{Ч}_t \quad (8)$$

$$\mathcal{Z}(\delta) = 1 - \mathcal{Z}_1\delta - \cdots - \mathcal{Z}_r\delta^r \quad (9)$$

$$\mathcal{A}(\delta) = \mathcal{A}_0 - \mathcal{A}_1\delta - \cdots - \mathcal{A}_s\delta^s \quad (10)$$

Where: λ =delay parameter; $\mathcal{A}$=impact parameter; $\mathcal{Z}$= the growth rate; $\mathcal{F}_t$ is the indicator variable.

2.3 Testing Unit Root

Prior to undertaking any advanced time series modeling, it is essential to formally assess the underlying properties of the series employed in the analysis [14]. The Augmented Dickey Fuller (ADF) test, which is grounded in a regression based framework, is commonly used for this purpose [11].

$$\mathcal{H}_t = \phi\mathcal{H}_{t-1} + \sum_{j=1}^{p-1}\mathcal{H}_j\Delta\mathcal{H}_{t-j} + \mathfrak{Ч}_t \quad (11)$$

Where $\mathcal{H}_t$ as defined above; p, the number of lagged differenced terms.

Statement of Hypothesis:
$H_0: \mathcal{S} = 0$ (Series has a unit root)
VS
$H_1: \mathcal{S} \neq 0$

Test statistics are:

$$t = \frac{\hat{\mathcal{S}}-1}{S.E(\hat{\mathcal{S}})} \sim t_{\propto}(n) \quad (13)$$

Remark: Rejection of the null hypothesis indicates that the time series does not have a unit root.

2.4 Model Diagnostics

Diagnostic evaluation constitutes a critical stage in the development of time series models, requiring a careful examination of multiple diagnostic measures to assess whether the fitted model is adequate and suitable for forecasting purposes. In this study, the following diagnostics are considered:

2.4.1 Plot Residual ACF & PACF

After fitting a suitable ARIMA model, its adequacy can be assessed by examining the ACF and PACF of the residuals. If the majority of the sample correlogram coefficients fall within the interval of $\left(\pm\frac{2}{\sqrt{n}}\right)$, where n denotes the length of the time series, the residuals can be considered white noise, suggesting that the model provides a satisfactory fit [14, 19, 21].

2.4.2 The Akaike Information Criterion

The Akaike Information Criterion (AIC) is defined [2, 18];

$$\text{AIC} = M_n\left[1 + \frac{2P}{n-P}\right] \quad (14)$$

Where:
$M_n =$ Index related to production error, known as residual sum of squares

$p =$ Number of parameters, $n =$ Number of observations.

2.4.3 The Bayesian Information Criterion

The Bayesian Information Criterion (BIC) [9, 17, 33] is commonly employed to select the most appropriate model from a finite set of candidates. When comparing two or more estimated models, the one with the lowest BIC value is considered the preferred choice. It is defined as follows:

$$\text{BIC} = \mathcal{r} ln\hat{\sigma}_e^2 + kln(\mathcal{r}) \quad (15)$$

Where $\hat{\sigma}_e^2$ is the estimated error variance defined by

$\hat{\sigma}_e^2 = \frac{1}{n}\sum_i^n (\mathcal{H}_i - \bar{\mathcal{H}})^2$

Where: $\mathcal{H}$ remained as earlier defined, $n =$ No. observations, $k =$ No. of parameters.

2.4.4 Ljung Box Test

The Ljung–Box test [14 – 16, 24] provides a method for assessing the presence or absence of serial autocorrelation in a time series up to a specified lag $\aleph$. Conducting this test involves computing the test statistic $\mho$ for a series $\{\mathcal{H}_t\}$of length n, as follows:

$$\mho(m) = n(n+2)\sum_{j=1}^{\aleph} \frac{r_j^2}{n-j} \quad (16)$$

Where: r_j = The accumulated sample autocorrelations, $\aleph$ = Time lag.

Statement Hypothesis: H_0: (autocorrelation does exist) vs H_1

3. Results and Discussion

3.1 Exploratory Data Analysis

The analysis of childhood malaria incidence in Table 1 presents several key statistical measures that provide insight into the distribution and characteristics of the data.

Table 1: Descriptive Statistics Childhood Malaria Incidence

	Childhood Malaria
Mean	277.6944
Standard Error	9.782885
Median	242.5
Mode	231
Standard Deviation	131.2512
Sample Variance	17226.87
Kurtosis	0.741941
Skewness	1.064228
Range	640
Minimum	91
Maximum	731
Sum	49985
Count	180
Confidence Level(95.0%)	19.30462

The mean incidence rate is 277.69, suggesting that this is the average number of cases observed. The median at 242.5 indicates that half of the observations fall below this value, which suggests some skewness in the data. The mode, which is 231, indicates the most frequently occurring incidence, suggesting that a significant number of cases cluster around this value. A standard deviation of 131.25 and a sample variance of 17226.87 indicate considerable variability in the incidence rates. A high standard deviation suggests that the data points are spread out over a wide range, which is further emphasized by the range of 640 (from a minimum of 91 to a maximum of 731). The skewness value of 1.064 indicates a right skew in the distribution, meaning that several instances with higher incidence rates are pulling the mean upwards compared to the median. The kurtosis of 0.74 suggests a distribution that is relatively flat compared to a normal distribution, implying fewer extreme values (outliers). Also, the 95% confidence interval of 19.30 around the mean indicates that we can be 95% confident that the true mean incidence rate falls within this range, emphasizing the precision of the estimate.

Table 2: Monthly Means of Childhood Malaria Incidence

S/N	Months	Monthly Total	Monthly Mean
1	January	4155	277
2	February	4055	270
3	March	4241	283
4	April	4037	269
5	May	3950	263
6	June	4173	278
7	July	4349	290
8	August	4450	297
9	September	4213	281
10	October	4447	296
11	November	3913	261
12	December	4002	267

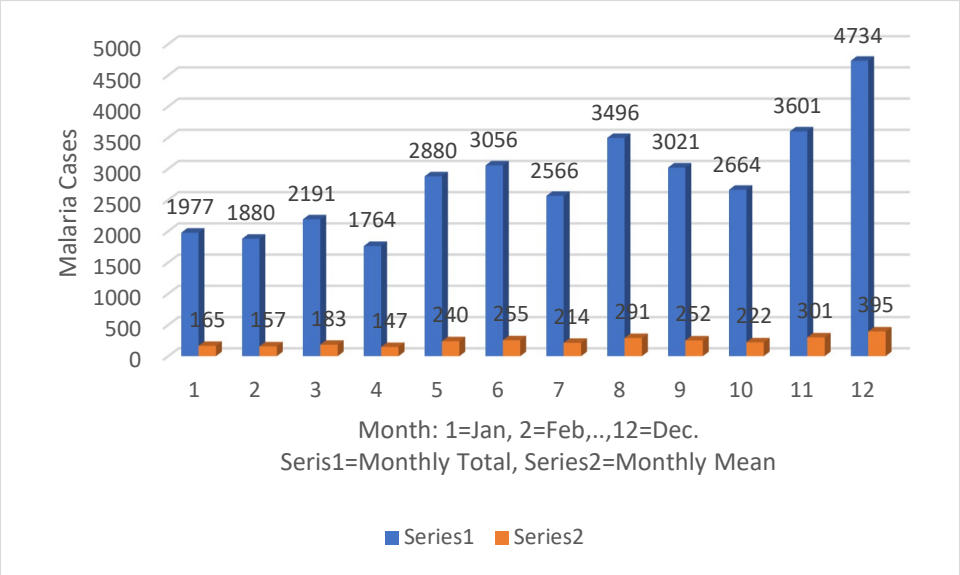

Figure 1: Monthly Totals and Means of Childhood Malaria Incidence

Table 2 and Figure 1 present monthly totals and means of malaria incidence over the study period. It shows a generally fluctuating trend, with totals ranging from 3,950 to 4,550 and means from 261 to 297. Notably, the highest total occurred in the month of August at 4,550 (mean of 297), while the lowest mean was 261 (total of 3913) in November, indicating variability in incidence levels.

Table 3 and Figure 2 present yearly totals and means of malaria incidence from 1977 to 2011. Overall, there has been a notable increase in both total cases and mean incidence over the years. The highest yearly total occurred in 2009, with 6,029 cases, and the highest mean was also recorded in the same year, as 502; the lowest yearly total occurred in 2000, with a mean of 147. This trend indicates a growing burden of malaria incidence over the observed period, highlighting the need for continued public health interventions.

Table 3: Yearly Means of Childhood Malaria Incidence

S/N	Years	Yearly Total	Yearly Mean
1	1997	1977	165
2	1998	1880	157
3	1999	2191	183
4	2000	1764	147
5	2001	2880	240
6	2002	3056	255
7	2003	2566	214
8	2004	3496	291
9	2005	3021	252
10	2006	2664	222
11	2007	3601	301
12	2008	4734	395
13	2009	6029	502
14	2010	4517	376
15	2011	5609	467

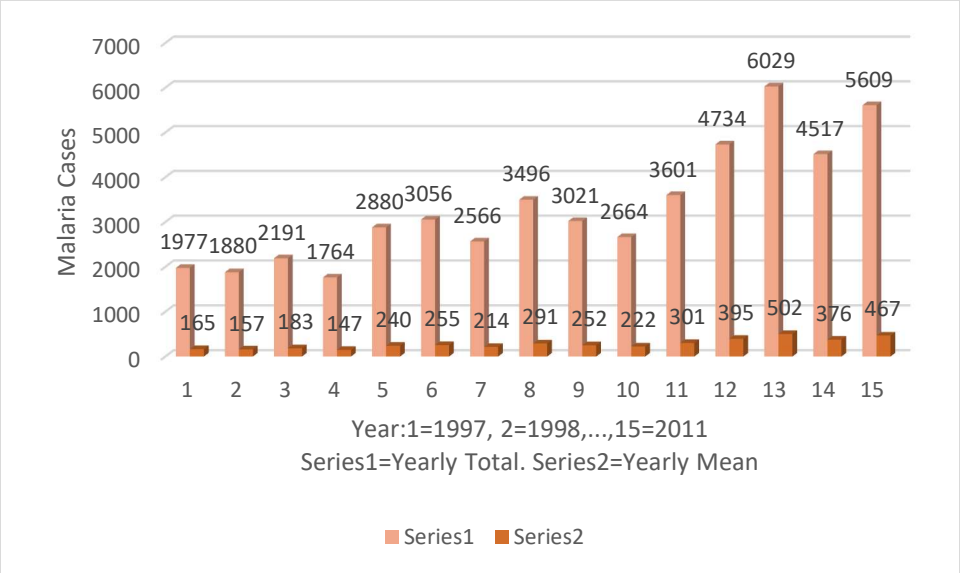

Figure 2: Yearly Totals and Means of Childhood Malaria Incidence

3.2 Intervention Modelling

3.2.1 Time Series Plot

Figure 3 is the time plot showing the monthly childhood malaria incidence from January 1997 to December 2011. The series rises and falls at random with an increasing trend pattern, with a sharp fall in October 2003, which called for intervention. According to indicator functions, the suspected location of the intervention is identified as:

$$\mathcal{F}^{T}{}_{t} = \begin{cases} 1, & t = October\ \ 2003 \\ 0, & t \neq October\ \ 2003 \end{cases} \qquad (17)$$

Here $T = December\ \ 2003$ and $\mathcal{F}^{T}{}_{t}$ is a Pulse function type.

The dataset is sectioned into periods belonging to "before the intervention" (pre-series) and "after the intervention" (post-series). Data points from January 1997 to September 2003 are used as the pre-series displayed in Figure 4, and datasets from October 2003 to December 2011 are used as the post-series.

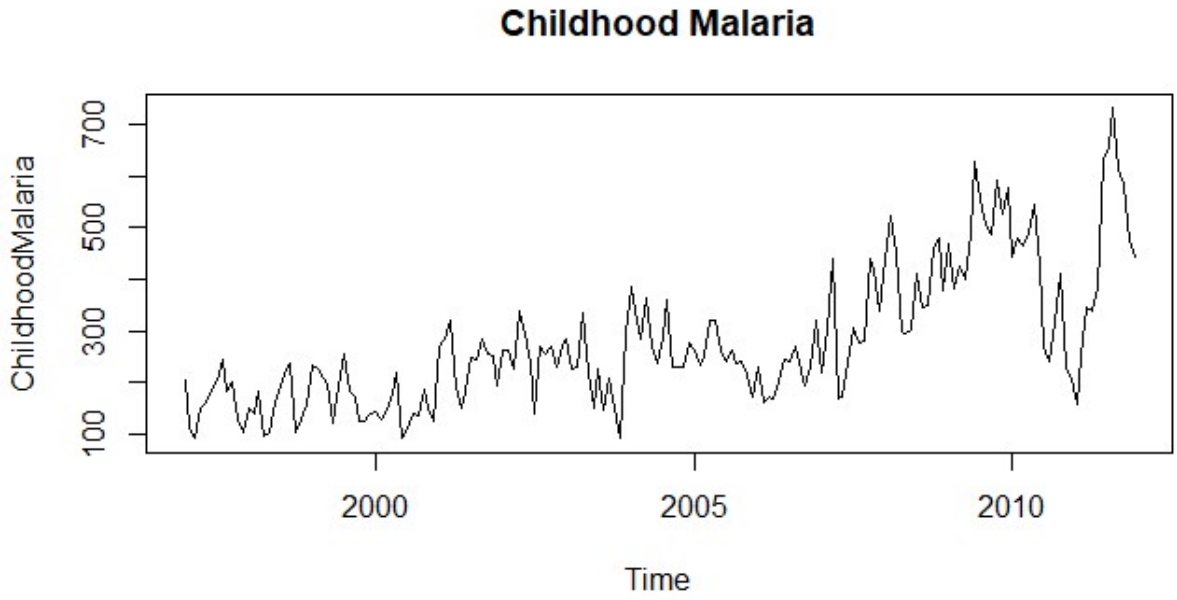

Figure 3: Time Plot of Childhood Malaria Incidence

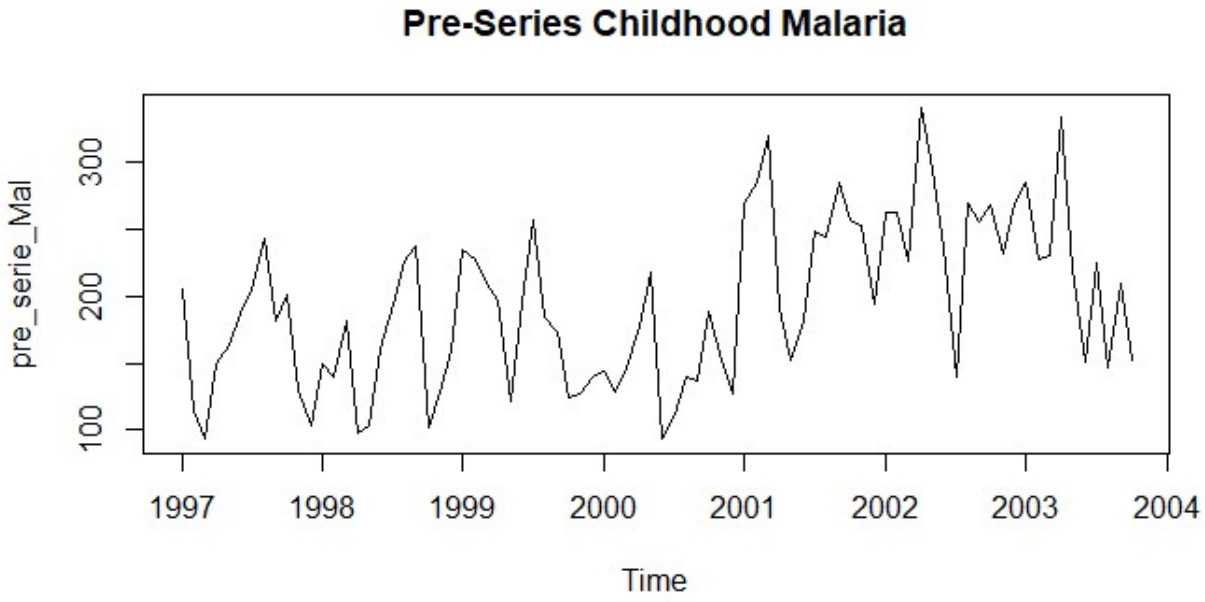

Figure 4: Time Plot of Pre-Series Childhood Malaria Incidence

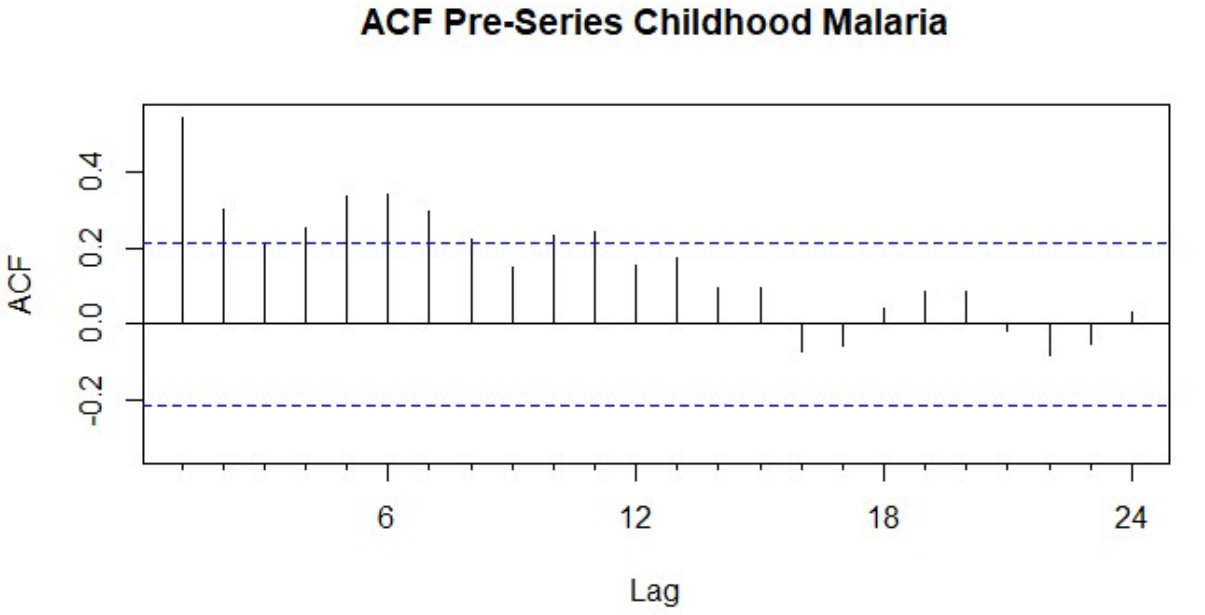

Figure 5: ACF Plot of Pre-Series

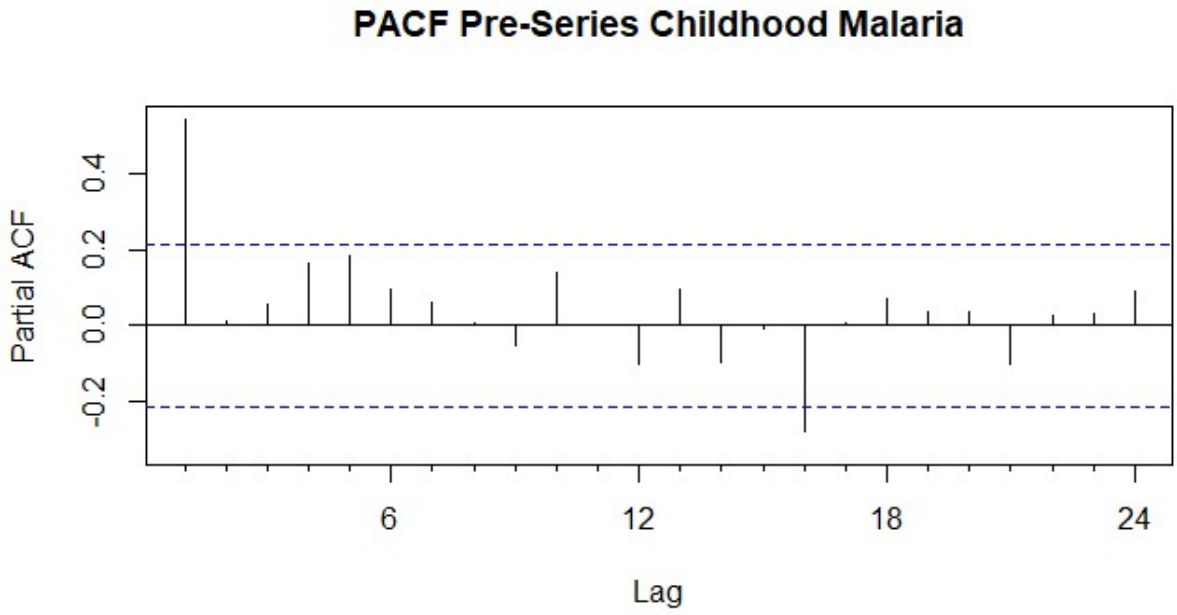

Figure 6: PACF Plot of Pre-Series

3.2.2 ARIMA Modelling

The pre-series data are used in determining the ARIMA form of the intervention structure. Pre-intervention time plots in Figures 4, 5, & 6 show that the series exhibits the characteristics of non-stationarity, which is verified by the unit root test statistics of -2.435 with a p-value of 0.3976 (>0.05) at the level in Table 4.

Table 4: Unit Root Testing

Test	Augmented Dickey-Fuller
Dataset	Pre-Series(childhood malaria)
Dickey-Fuller statistic	-2.435
Lag order	4
P-value	0.3976
H_1	Stationary

To achieve stationarity, the series is transformed using the differencing method (∇^L), with a single differencing applied. The plot of the differenced series, shown in Figure 7, confirms that the series has become stationary. The results of a unit root test on the first differenced series further verified its stationarity, as the p-value of the test statistic was below the significance threshold $(0.01 < 0.05)$, as shown in Table 5. Using the correlogram of the differenced series presented in Figures 8 and 9, five candidate ARIMA models were tentatively identified, with their corresponding statistics summarized in Table 6. The suitability of the $ARIMA(0,1,2)$ model is supported by the observation that the autocorrelation coefficients of its residuals remain within the significance limits of $(-0.2222,0.2222)$, as shown in Figure 10. Additionally, this model exhibits the lowest BIC and AIC values, 878.785 and 871.6017, respectively, as reported in Table 7, further confirming its adequacy. The results of the Ljung-Box test, shown in Table 8, produced a p-value of 0.4911, providing further support for the suitability and statistical adequacy of the model for the dataset. Forecasts generated using the $ARIMA(0,1,2)$ model closely matched the observed values in the post-sample period, indicating accurate predictive performance.

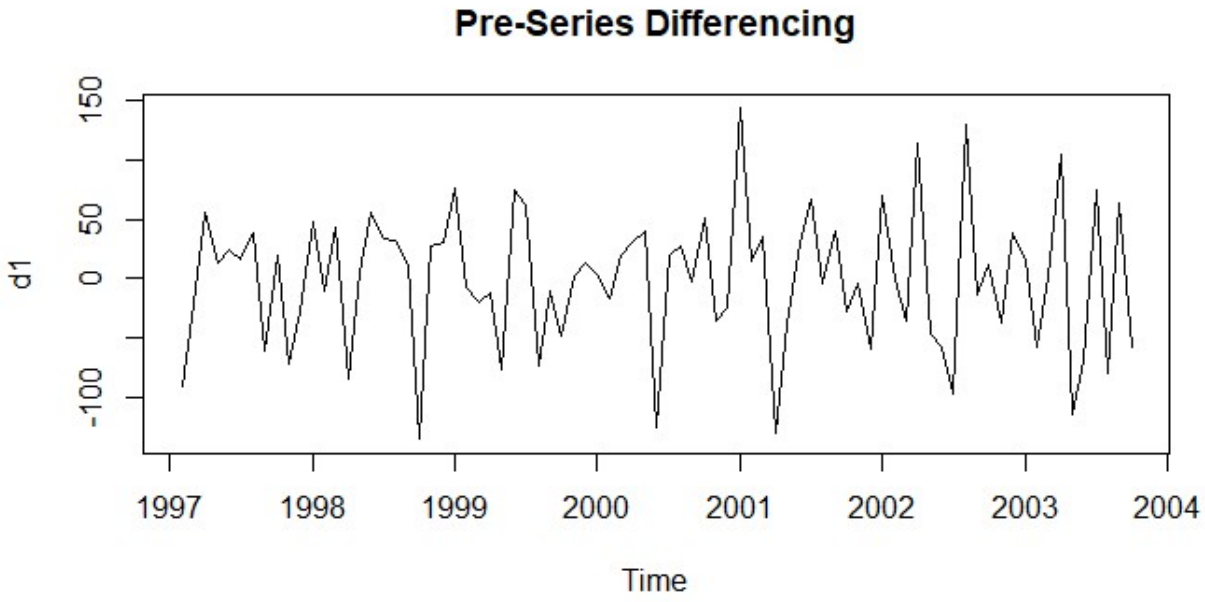

Figure 7: Plot of Pre-Series at First Difference

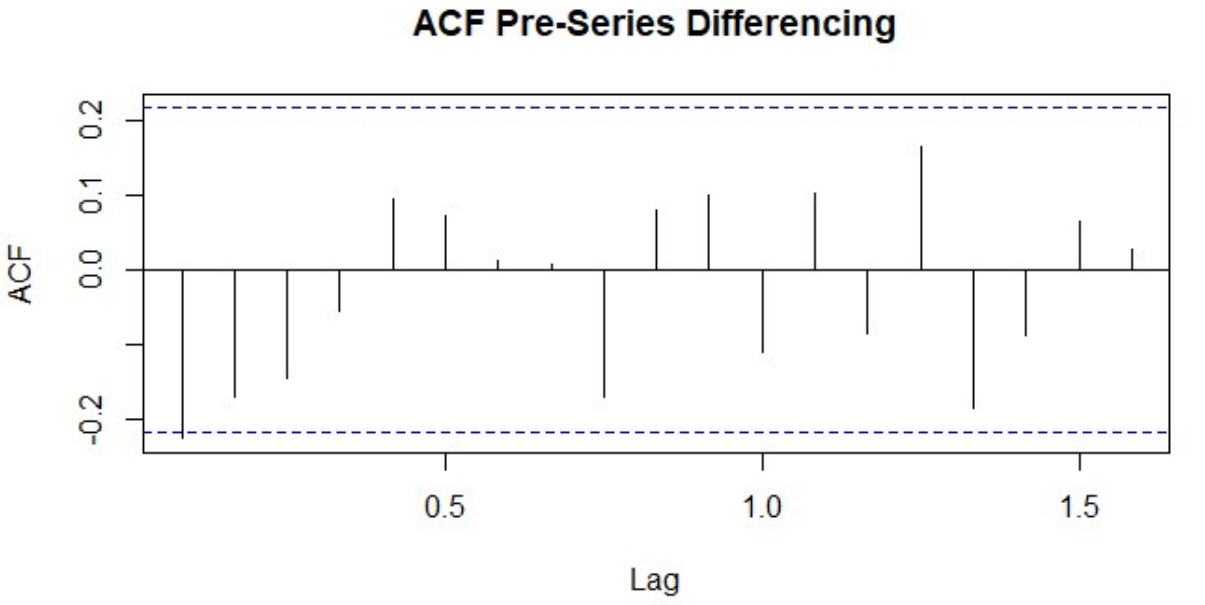

Figure 8: ACF Plot of Pre-Series at First Difference

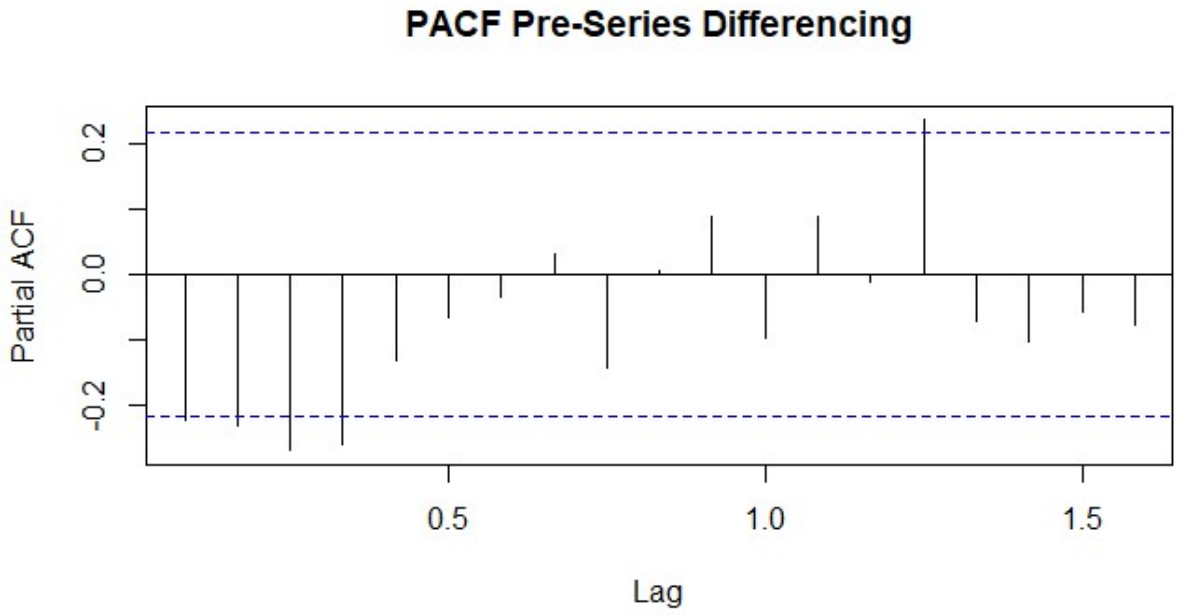

Figure 9: PACF Plot of Pre-Series at First Difference

Table 5: Unit Root Test at First Difference

Test	Augmented Dickey-Fuller
Dataset	Pre-Series (childhood Malaria)
Dickey-Fuller statistic	-6.4821
Lag order	4
P-value	0.01
H_1	Stationary

Table 6: Parameter Estimation for ARIMA Models

$ARIMA(p, \mathcal{L}, q)$		Estimate	Std. Error	Z-value	Prob. Value
(1,1,0)	$\mathcal{S}_1$	-0.23257	0.10972	-2.1196	0.03404 *
(2,1,0)	$\mathcal{S}_1$	-0.28854	0.10974	-2.6293	0.008557 **
	$\mathcal{S}_2$	-0.24173	0.10961	-2.2054	0.027427 *
(0,1,1)	$\mathcal{V}_1$	-0.72558	0.10741	-6.7555	1.424e-11 ***
(0,1,2)	$\mathcal{V}_1$	-0.50842	0.10508	-4.8382	1.31e-06 ***
	$\mathcal{V}_2$	-0.29188	0.10325	-2.8268	0.004701 **
(1,1,1)	$\mathcal{S}_1$	0.373229	0.137709	2.7103	0.006723 **
	$\mathcal{V}_1$	-0.894622	0.073614	-12.1529	2.2e-16 ***

Table 7: Model Evaluation for ARIMA Models

Model	BIC	AIC
ARIMA(0,1,2)	878.785	871.6017
ARIMA(1,1,1)	879.2512	872.0678
ARIMA(0,1,1)	881.8307	877.0418
ARIMA(2,1,0)	891.2904	884.107
ARIMA(1,1,0)	891.6039	886.815

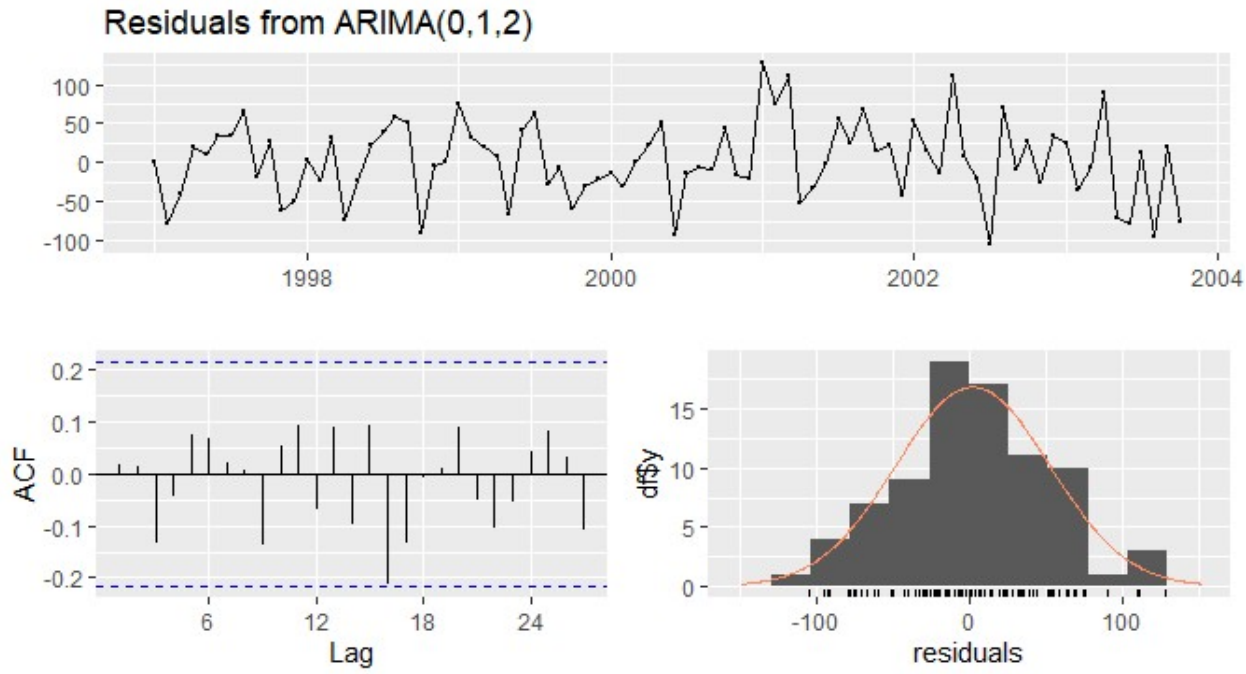

Figure 10: Residual from ARIMA(0,1,2) Model

Table 8: Ljung-Box Testing

Residuals from ARIMA(0,1,2)
Q* = 13.454, df = 14, p-value = 0.4911
Model df: 2. Total lags used: 16

3.2.3 ARIMA-Intervention Modelling

In Table 9, the model gives $\mathcal{A} = -119.8$ with a p-value of 0.0285, the estimate is significantly different from zero, while the direction of change is negative. The rate of decay, that is, the rate at which the post-intervention level returns to the pre-intervention level, is estimated to be zero; this implies a rapid return. However, the intervention effect has a delay of 2 periods. With the estimated value of the impact parameter, this implies that the level of childhood malaria cases dropped by nearly 120 hospital-admitted cases a month after the RBM initiative.

The ARIMA(0,1,2) intervention model is represented mathematically as

$$\mathcal{H}_t = -119.8\mathcal{F}_{t-2} + (1 - 0.25\delta - 0.25\delta^2)\text{Ч}_t \qquad (18)$$

Validation through Ljung-Box Q Statistics yielded a p-value (0.5722) exceeding the alpha threshold of 0.05, signifying the absence of autocorrelation in the model, see Table 10. Therefore, the model in (18) is statistically significant and statistically adequate at a 5% significance level. The forecasts plot derived from the fitted model, compared with the observed values, provides additional confirmation of the adequacy of the model in (18), as the predicted values closely matched the actual data, as illustrated in Figure 12.

Table 9: Parameter Estimation for ARIMA(0,1,2)-Intervention Models

Parameter	Estimate	Std. Error	Z-value	Prob. Value
$\mathcal{V}_1$	-0.250546	0.073757	-3.3969	0.0006815 ***
$\mathcal{V}_2$	-0.252818	0.077762	-3.2512	0.0011494 **
$\mathcal{A}$	-119.791529	54.674804	-2.1910	0.0284531 *
λ	2			

Table 10: Ljung-Box Test for ARIMA(0,1,2)-Intervention Model

Residuals from ARIMA(0,1,2)-INTERVENTION
Q* = 20.173, df = 22, p-value = 0.5722
Model df: 2. Total lags used: 24

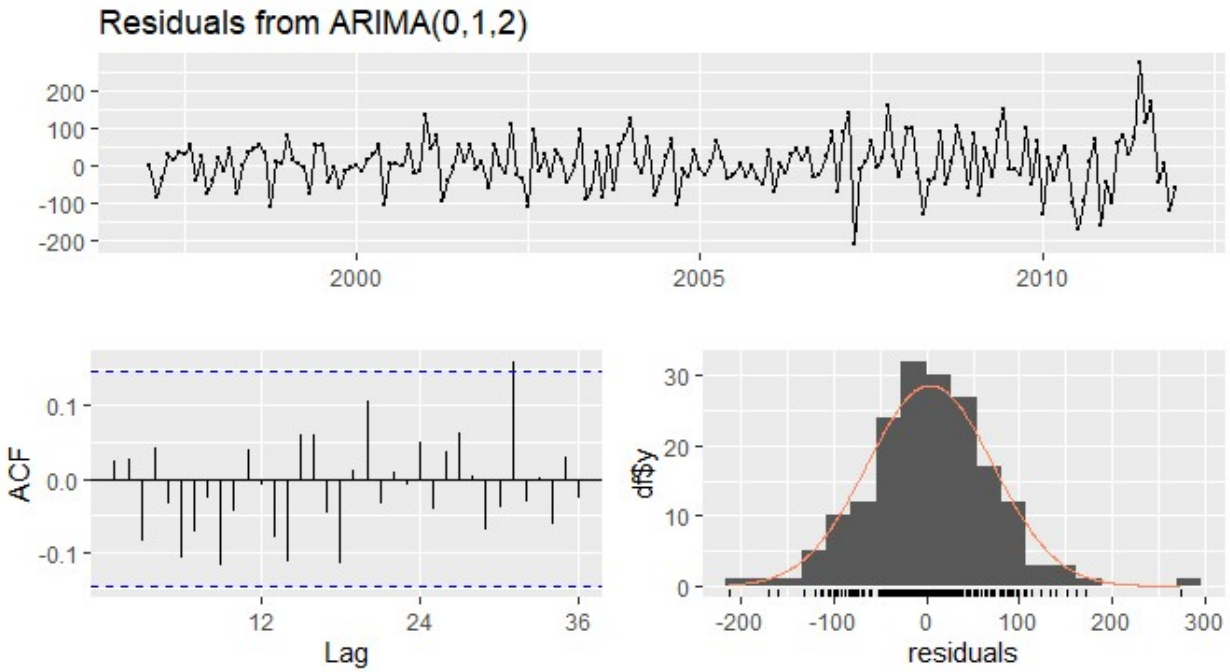

Figure 11: Residual from ARIMA(0,1,2)-INTERVENTION Model

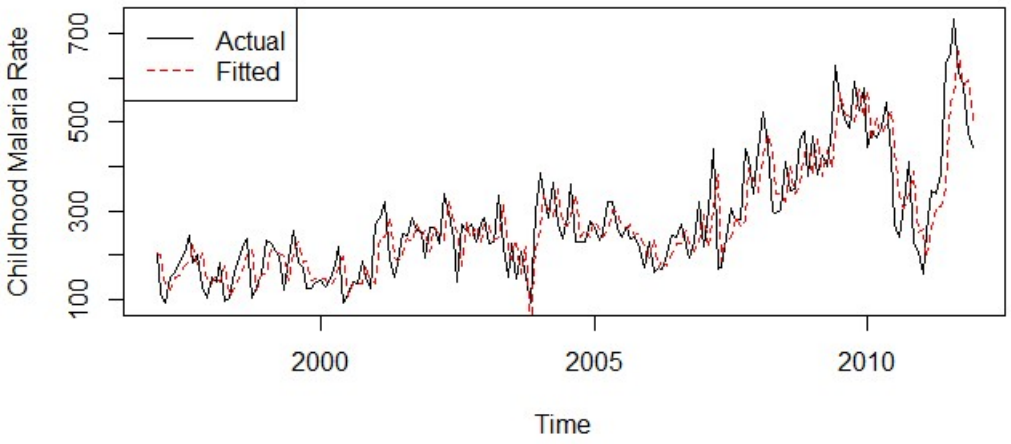

Figure 12: Fitted Model Forecast Vs Actual Values

4. Conclusion

This study provides a comprehensive analysis of childhood malaria incidence, revealing significant insights into the trends and variations over time. The exploratory data analysis indicated a mean incidence rate of 277.69, with considerable variability as reflected in the standard deviation of 131.25. The right skewness of the data highlights higher incidence cases, necessitating targeted public health interventions to address these outliers effectively.

Temporal trends illustrate an alarming increase in malaria cases from 1977 to 2011, particularly peaking in April 2002 (pre-intervention) and August 2011 (post-intervention), which underscores the pressing need for continued and enhanced public health strategies. Monthly and yearly analyses further revealed fluctuations in incidence, with pronounced peaks during August and the year 2009, suggesting potential seasonality that could inform preventative measures.

The intervention modelling component of the study, particularly the ARIMA analysis, confirmed the non-stationarity of the pre-intervention data, necessitating transformations to achieve stationarity. The establishment of the ARIMA(0,1,2) model, validated by various statistical tests, provides a robust framework for understanding the dynamics of malaria incidence before and after the intervention. The significant negative impact parameter indicates that the RBM initiative has effectively reduced the incidence of malaria, with a notable decline of approximately 120 cases per month post-intervention. However, the intervention had only a temporary impact as the growth rate is noted with a value of zero. This shows that the RBM organizers and the Nigerian Government, in partnership with health professionals, had worked vigorously after the disbursement of the RBM fund by the Global Fund, but, after a while, relaxed intervention due to poor funding.

Overall, the findings emphasize the necessity for sustained public health initiatives, especially during peak transmission periods, to mitigate the burden of childhood malaria. This study lays the groundwork for further investigations aimed at improving public health outcomes and enhancing strategies for malaria control among vulnerable populations.

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