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Childhood URTI Intervention Assessment: A Box-Tiao Time Series Approach

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Abstract: This study applied the Box-Tiao ARIMA-based intervention analysis in assessing government interventions in childhood upper respiratory tract infections (URTIs) for a period of 15 years. Results revealed seasonal variations in URTI incidence, with peaks during the Dry season, especially from January to March, and a reduction during the Wet season, from April to August. Exploratory data analysis shows a right-skewed distribution of URTI severity, with a mean of 88.48 and significant variability in the studied dataset. A pulse-type intervention was introduced in May 2006 as a measure to eradicate childhood URTI. The pre-intervention series was stationary at level with an ARIMA (1, 0, 0) model fitted. The impact parameter was insignificant, with a value of -22.410200 and a p-value of 0.5716. The May 2006 intervention had no significant effect on URTI eradication, as more youngsters were still infected with an increasing hospital admitted cases in the post-intervention period. These findings suggest that environmental factors significantly influence the occurrence of URTIs, and while interventions may not always have an immediate effect, ongoing public health strategies are needed to address the rising burden of childhood respiratory infections in the State.

Keywords: Childhood URTI, Statistical Assessment, Time Series, Box-Tiao Model.

INTRODUCTION

Despite the fact that Nigeria has an abundance of natural and human resources, it has been one of the least successful African nations in improving child survival during the last forty years. Preventable childhood killer diseases claim the lives of at least one million Nigerian children each year, primarily those under the age of five (UNICEF, 2009). Childhood illnesses put millions of children's lives in danger worldwide, impede the development of the economy and social services, and cause sorrow for the patients, their families, their communities, and the nation as a whole.

Children aged 0 to 14 years old are susceptible to upper respiratory tract infections, which are among the most common childhood illnesses. An upper respiratory tract infection (URTI) is an illness caused by an acute infection, which involves the upper respiratory tract, including the nose, sinuses, pharynx, larynx, or trachea. This commonly includes nasal obstruction, sore throat, tonsillitis, pharyngitis, laryngitis, sinusitis, otitis media, and the common cold. Most infections are viral in nature, and in other instances, the cause is bacterial. URTIs can also be fungal or helminthic in origin, but these are less common (Guibas and Papadopoulos (2017), Ellis (1998), Pokorski (2015), and Heymann (2015)).

Regrettably, a lot of illnesses appear to have a particular interest in attacking youngsters more frequently and forcefully than they do to adults. There are several reasons why illnesses can affect children more severely. Children are more susceptible to diseases than adults because they are frequently exposed and have not yet developed the immune systems needed to fight off certain illnesses (Perlin and Cohen, 2002). In light of these, the Akwa Ibom State government has allocated significant financial resources in the previous administrations to the Ministry of Health, particularly in the area of providing free medical services to the elderly, children, and pregnant women across the state. The goal of these efforts is to guarantee that healthcare is not only accessible and affordable but also that no one dies from diseases that could be preventable.

Therefore, the objective of this study is to assess the impact of government interventions on childhood upper respiratory tract infections (URTIs) by building and applying a suitable time series structure in modelling the dataset.

Researchers and many scholars have studied modelling and forecasting the prevalence of URTI cases; Chew *et al*. (1998) evaluated the seasonal trends of viral respiratory tract infections in a tropical environment in Singapore from September 1990 to September 1994. Results revealed that respiratory tract viral outbreaks, particularly among infants who required hospitalization, were found to be associated mainly with respiratory syncytial infection (72%), influenza (11%), and parainfluenza viruses (11%). Spaeder and Fackler (2011) used a time series model to predict the burden of viral respiratory illness in a pediatric intensive care unit. Their results suggest that time series models may be useful tools in forecasting the burden of severe viral respiratory illness at the institutional level, helping institutions make decisions to optimize the distribution of resources. Effiong and Ebong (2016) Studied multivariate time series modelling of selected childhood diseases in Akwa Ibom State. Their results revealed that the VAR (1) model fitted well, and the model revealed that upper respiratory tract infection, pneumonia, and anemia are linked to or caused by malaria. Ibraheem *et al*. (2020) investigated the burden and spectrum of pediatric respiratory diseases at a referral hospital in north-central Nigeria. Their results revealed that pneumonia and aspiration pneumonitis are major contributors to morbidity and mortality due to respiratory disease, for which interventions towards improving childhood health indices should be prioritized. Mailepessov *et al*. (2021) used the time series technique to analyze the short-term association between climatic variables and acute respiratory infections in Singapore. Their results revealed that lower temperatures increase the risk of ARIs. Inyang *et al*. (2024b) created a time series model for the pediatric anemia burden while investigating the government's intervention. Their findings revealed that the intervention was not successful in producing the intended result. Calderaro *et al*. (2022) examined respiratory tract infections and laboratory diagnostic methods. They remarked that the implementation of molecular methods with syndromic panels has the potential to be a powerful decision-making tool for patient management, despite requiring appropriate use of the test in different patient populations. Lim *et al*. (2023) used high-dimensional time series data and forecast combinations in forecasting the upper respiratory tract infection burden. They showed that forecast combinations of five other forecasting models had better and more consistent predictive performance than other modelling approaches over periods with and without structural breaks in transmission dynamics.

A framework for evaluating the impacts of an intervention on a time series is provided by intervention model building, which was developed by Box and Tiao (1975). The process is thought to be affected by the intervention by changing its mean level. Therefore, it may be anticipated that the post-change level will differ from the pre-change level. As a result, by examining the mean functions of the relevant stochastic process, we may investigate these consequences. Scholars who successfully applied the Box-Tiao techniques in modelling include Deutsch and Alt (1977), who examined the effect of Massachusetts' gun control law on gun-related crimes in the City of Boston. Sharma and Khare (1999) used an intervention analysis model to study the impact of the intervention introduced by the Indian government to control the pollution caused by vehicular exhaust emissions. Girard (2000) applied the ARIMA model with intervention to analyze the epidemiological situation of whooping – cough in England and Wales for the period of 1940–1990. Nelson (2000) uses an ARIMA intervention analysis to estimate the impact of the Bankruptcy Act of 1978. Lai and Lu (2005) used an intervention model to look at the impact of the September 11, 2001, terrorist attack on air transport passenger demand in the USA. Min (2008) applied intervention analysis to assess whether two events, the 9–21 earthquake in 1999 and the Severe Acute Respiratory Syndrome (SASS) outbreak in 2003, had a temporary or long–term impact on the inbound tourism demand from Japan. Lam *et al*. (2009) used a time series intervention ARIMA model to measure the intervention effects and the asymptotic change in the simulation results of the business process reengineering that is based on the activity model analysis. Jarrett and Kyper (2011) examined the impact of the world financial crisis (WFC) on the Chinese stock price. Darkwah *et al*. (2012) use intervention time series analysis to assess the nature and impact of the establishment and operations of community policing in communities in Ghana. Mrinmoy *et al*. (2014) assessed the impact of Bt–Cotton variety on cotton yield in India. With step intervention, was the introduction of Bt–Cotton variety in 2002. Yang (2014) used ARIMA with an intervention model to analyze the impact of new product releases on revenue. Shittu and Inyang (2019) modelled Nigerian monthly crude oil prices using the ARIMA-Intervention model to compare the result with that of the intervention model using lag operator. Etuk *et al*. (2022) investigated the impact of the declaration of cooperation on Nigerian crude oil production. Moffat and Inyang (2022) investigated the impact of the Nigerian government amnesty programme on crude oil production. Inyang *et al*. (2022) studied the effect of global oil politics on the Nigerian oil price using the Box–Tiao approach. Results revealed that the December 2016 intervention by the Organization of Petroleum Exporting Countries had a significant and abrupt impact on the Nigerian oil price after its introduction, with an associated increment of 33.72%. Inyang *et al*. (2023) used a time series intervention model based on the ESM and ARIMA Models to model the daily Pakistan rupee to Nigerian naira exchange rates.

Masena *et al.* (2024a) estimated the impact of the COVID-19 pandemic on the South African total monthly wholesale and retail sales. Their results revealed that the pandemic had an immediate and severe negative effect on wholesale and retail trade sales with a corresponding duration of 15 and 8 months, respectively. Again, Masena *et al.* (2024b) investigated the lingering negative effect of COVID-19 on the South African Rands. Findings revealed a total estimated loss of 130,579 million in sales during the intervention period of 52 months. Inyang (2024) and Inyang *et al*. (2024a) incorporate the exponential smoothing method into the intervention architecture in modelling the Nigerian naira exchange rates in the face of an economic downturn. However, the intervention model with ARIMA structure outperformed the exponential smoothing method formulation.

MATERIALS AND METHOD

Data Description

The data used in this study are the monthly childhood URTI cases spanning from January 1997 to December 2011, obtained from records in five hospitals selected from the state's three senatorial districts in Akwa Ibom State. The dataset was divided into observations belonging to pre-intervention (January 1997 to April 2006) and post-intervention periods (May 2006 to December 2011). The statistical package used for the analysis of this work is the R language (R Core Team, 2022).

Model Specification

The most popular method for modeling and forecasting has been identified as the Box-Jenkins ARIMA model, or ARIMA(p, d, q) (Box and Jenkins (1970, 1976), Box *et al*. (1994)). However, the ARIMA model's ability to forecast may be compromised when external events have an impact on the time series. Consequently, the ARIMA-Intervention analysis introduced by Box and Tiao (1975) is recommended, given as:

$$\int_t = \zeta(L) + \coprod_t \qquad (1)$$

Where $\zeta(L)$ is the transfer function component and $\coprod_t$ is noise component

Intervention model with ARIMA

$$\int_t = \frac{\vartheta(L)L^d}{F(L)}\mho_t^T + \frac{\beta(L)}{\alpha(L)}\eta_t \qquad (2)$$

Since $\zeta(L) = \frac{\vartheta(L)L^d}{F(L)}\mho_t^T$ and $\coprod_t = \frac{\beta(L)}{\alpha(L)}\eta_t$

Where:

$$\alpha(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha p L^p \text{ and}$$

$$\beta(L) = 1 - \beta_1 L - \beta_2 L^2 - \ldots - \beta p L^q$$

$$F(L) = 1 - F_1 L - \ldots - F_r L_r \text{ and } \vartheta_0 - \vartheta_1 L - \ldots - \vartheta_s L^s$$

$\int_t$ is the childhood URTI series at time t, d = delay parameter, ϑ = impact parameter, F = the growth rate, α = non-seasonal autoregressive parameter, β = non-seasonal moving average parameter, η_t = white noise.

$\coprod_t$ is a Box – Jenkins ARIMA(p, d, q) model which represents the baseline monthly childhood URTI series in pre-intervention period.

$\mho_t^T$ is the indicator variable. Mathematically, they are written as

$$\mho_t^T = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases} \qquad (3)$$

$\mho_t^T$ is called the Pulse function.
Hence, (2) becomes

$$\int_t = \frac{\vartheta(L)}{F(L)}\mho_{t-d}^T + \frac{\beta(L)}{\alpha(L)}\eta_t \tag{4}$$

Unit Root Test

As a prerequisite for any further analysis in time series modeling, it is pertinent to formally diagnose the characteristics of the series that are used in the study.

The Augmented Dickey-Fuller (ADF) test is based on the regression equation (Dickey and Fuller, 1979):

$$\int_t = \alpha\int_{t-1} + \sum_{j=1}^{p-1}\int_j \Delta\int_{t-j} + \eta_t \tag{5}$$

Where $\int_t$ is the series being tested and p is the number of lagged differenced terms included to capture any autocorrelation.

Hypothesis:

$H_0 = \beta = 0$ (series contains a unit root)

Against

$$H_1 = \beta \neq 0$$

Test statistics are:

$$T_\rho = \frac{\hat{\alpha}-1}{S.E.(\hat{\alpha})} \sim t_\propto(n) \tag{6}$$

If the null hypothesis is rejected, we conclude that the series contains no unit root.

Model Validation

Diagnostic test is an important step in time series model building and this consists of scrutinizing a variety of diagnostics to determine whether the selected model is healthy and hence ready to forecast (Inyang *et al*. (2024c)). We consider here;

Plot of the residual ACF

Once an appropriate ARIMA model is fitted, one can examine the goodness of fit by means of plotting the ACF of the residuals of the fitted model. If most of the sample autocorrelations coefficients of the residuals are within the bound of $\pm\frac{2}{\sqrt{T}}$, where T is the series length then the residuals are white noise indicating that the model is a good fit (Inyang *et al*. (2024a, 2024b, 2024c)).

Akaike Information Criterion (AIC)

The AIC (Akaike (1974)), is formulated as

$$\text{AIC} = M_T\left[1+\frac{2P}{T-P}\right] \tag{7}$$

Where:

M_T = Index related to production error (known as residual sum of squares)

p = No of parameters in the model, T = No. of data points.

Bayesian Information Criterion (BIC)

The BIC is a criterion for model selection among a finite set of models. Given any two or more estimated models, the model with the lowest value BIC is the one to be preferred (Schwarz (1978), Clement (2014)). It is given by:

$$\text{BIC} = n\ln\hat{\sigma}_\eta^2 + k\ \ln(n) \tag{8}$$

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

$$\hat{\sigma}_\eta^2 = \frac{1}{T}\sum_i^T(\int_i - \bar{\int})^2$$

$\int$ = Observed data, t = number of observations, k = Number of free parameters to be estimated.

Ljung Box Test

The Ljung Box Test is a way to test for the absence of serial autocorrelation, up to lag k.

To run the Ljung Box test, you must calculate the statistic Q (Ljung and Box, 1978). Given a series $\int_t$ of length ς:

$$Q(m) = \varsigma(\varsigma+2)\sum_{j=1}^{\aleph}\frac{r_j^2}{\varsigma-j} \tag{9}$$

Where: r_j = accumulated sample autocorrelations, $\aleph$ = the time lag.

Hypothesis

H_0 : (residuals do not show any autocorrelation)

Against

H_1 : (H_0 is false)

RESULTS AND DISCUSSIONS

An exploratory analysis of the childhood URTI data is carried out to gain a deeper understanding of the population's health status. Table 1 presents the analysis of childhood URTI with several important statistical measures. The highest monthly number of recorded cases of childhood URTI was 250 which happened in February 1997 and March 2011, while the lowest incidence, 8, was recorded in 1999. This sickness affected 15,926 youngsters in all, ranging in age from 0 to 14.

Table 1: Descriptive Statistics

Mean	88.47778
Standard Error	4.385218
Median	69
Mode	39
Standard Deviation	58.83387
Sample Variance	3461.424
Kurtosis	0.527352
Skewness	1.117209
Rang	242
Minimum	8
Maximum	250
Sum	15926
Count	180

The mean value of 88.48 implies that the average value for the measure of interest across the 180 subjects is 88.48 and this suggests that, on average, youngsters experience URTI-related metrics such as symptom severity, healthcare visits, or treatment cost at a moderate level. A relatively small standard error of 4.39 indicates that the sample mean is reasonably representative of the population mean. The median is 69 and its position below the mean indicates a right-skewed distribution, suggesting that while the average infant may have a higher URTI-related metric, there are some children experiencing much lower values, which pulls the median lower. The mode of 39 is significantly lower than both the median and mean and this further confirmed a right-skewed distribution.

A standard deviation of 58.83 (square root of the variance $(\sqrt{3461.42})$) indicates that the data points are widely spread out from the mean. In this case, high variability suggests that the population experiences a broad range of URTI-related outcomes, with some youngsters likely experiencing severe cases requiring extensive medical intervention and others having mild cases that require minimal care. A wide range of 242 highlights the diversity in the dataset.

A kurtosis value of 0.53 means that the distribution is relatively flatter than a normal distribution, this indicates that there are fewer outliers than might be expected in a normal distribution. And this could imply that the severity of URTI incidence is not excessively high or low, but moderately distributed. A skewness of 1.12 indicates a positively skewed distribution pulling the mean to a higher value than the median. This implies that while most infants experience lower levels of URTI severity, a small number of youngsters experience much more severe cases.

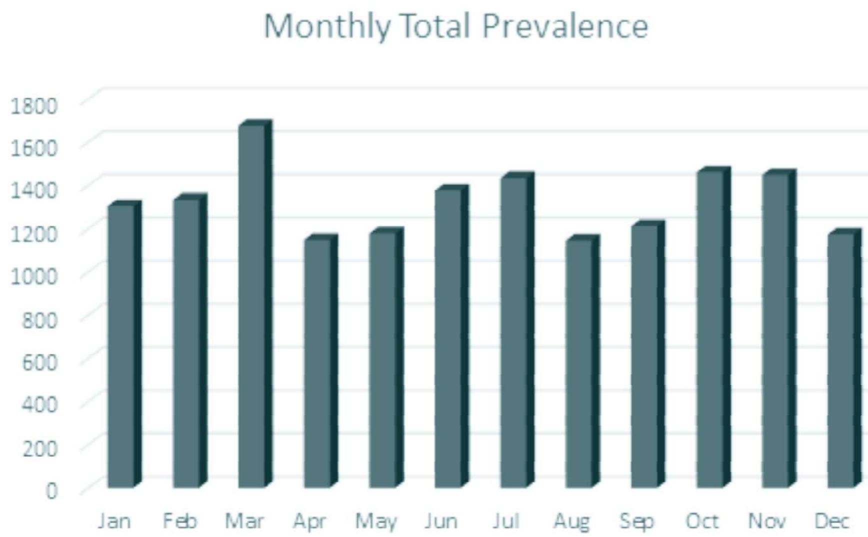

Figure 1: Monthly Totals of Childhood URTI

Figure 1 displays the incidence of childhood URTIs reported each month. These totals suggest a monthly variation in URTI occurrences, which may be driven by seasonal factors, changes in the weather, or other environmental influences. The months of January, February, and March have higher URTS incidence, with March peaking at 1680 cases. This is consistent with the seasonal pattern of URTIs, as respiratory infections tend to increase during this period. The environmental conditions during the Dry season, including dust from the Harmattan winds, low humidity, and high temperatures, could contribute to increased respiratory distress, triggering a rise in infections.

The decrease from April to August is consistent with the typical reduction in respiratory problems during the wet season (with factors such as increased humidity and more clean air due to rain), though the cases are still relatively high, ranging from 1148 to 1437 cases. Whereas from September to December, there is a gradual increase in URTI incidence (ranging from 1176 to 1463), again aligning with the onset of the Dry season.

The trend of increasing incidence in the latter half of the could be due to a combination of environmental factors and the academic calendar, where children are often in close contact in classrooms, potentially facilitating the spread of respiratory infections.

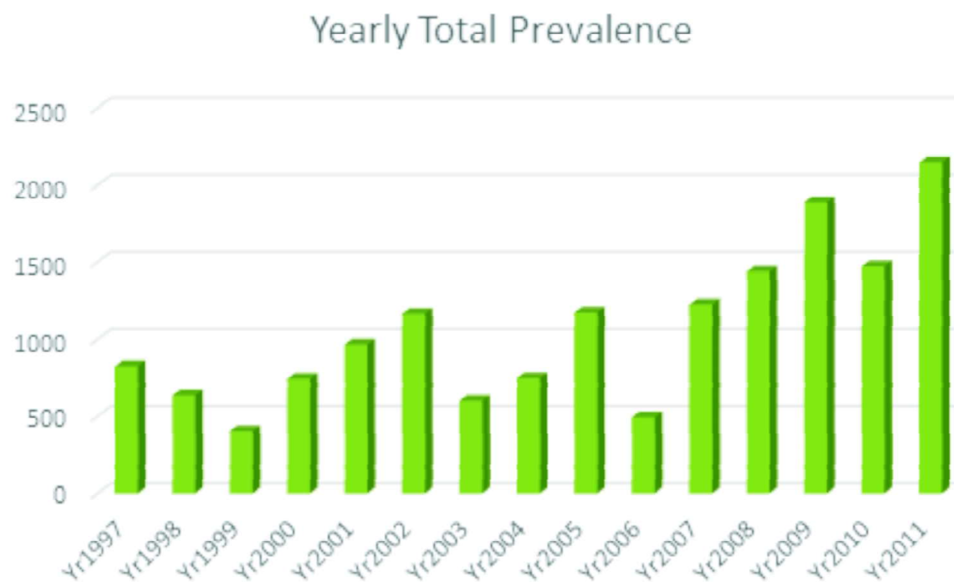

Figure 2: Yearly Totals of Childhood URTI

Figure 2 displays the incidence of childhood URTIs reported over a 15-year period. There is a clear decline in the number of URTI cases from 1997 to 1999, with a drop from 824 in 1997 to just 405 in 1999. After 1999, there was a steady increase in reported URTI cases, with cases consistently rising from 742 in 2000 to 2147 in 2011 but 2006 saw a sharp drop to 494 cases, indicating the year of intervention. This significant upward trend suggests a potential increase in the overall burden of pediatric respiratory infections over the years. Factors contributing to this increase could include population growth, urbanization, changes in viral patterns, or reduced effectiveness of preventive measures like vaccination or improved sanitation.

TIME SERIES MODELLING

Time Plot

The time plot showing the monthly URTI cases from January 1997 to December 2011 is displayed in Figure 3. The graph of the series does not show any recognizable pattern, as it rises and falls at random. But after a sharp decline in May 2006, an increasing upward trend has been observed since the last period.

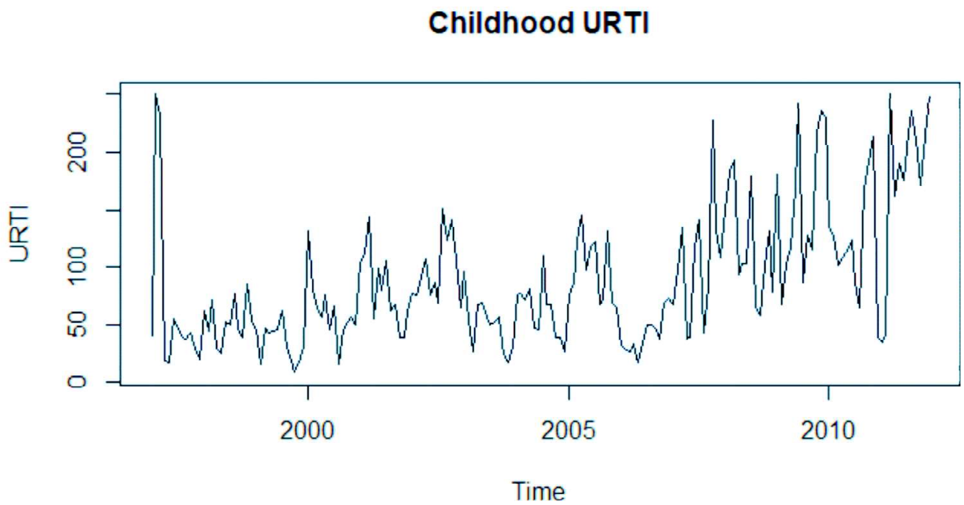

Figure 3: Time Plot of Childhood URTI

Intervention Modelling

The ARIMA-intervention model in equation (4) is used to model the dataset. The suspected point where the intervention took place is labelled by indicator functions as:

$$\mho_t^T = \begin{cases} 1, & t = \text{May 2006} \\ 0, & t \neq \text{May 2006} \end{cases} \tag{10}$$

Where: T = May 2006 and $\mho_t^T$ is the Pulse function type.

Pre-Intervention Modelling

Data on monthly childhood URTI cases from January 1997 to April 2006 is used for pre-intervention ARIMA model fitting, and data from May 2006 to December 2011 has been used to determine the intervention component form.

In the pre-intervention time plot shown in Figure 4, the graph of the series exhibits the characteristics of stationarity. The ability of both the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series to die out completely confirmed that the series is stationary (Figures 5 and 6), respectively. A unit root test at level further confirmed that the series is stationary since the p-value of the Augmented Dickey-Fuller Test is less than the alpha level (that is, p-value = 0.01768 < 0.05), Table 2.

Table 2: Unit Root Test at Level

Test	Augmented Dickey-Fuller
Data	Pre-Series Childhood URTI
Dickey-Fuller	–3.878
Lag order	4
P-value	0.01768

Alternative hypothesis Stationary

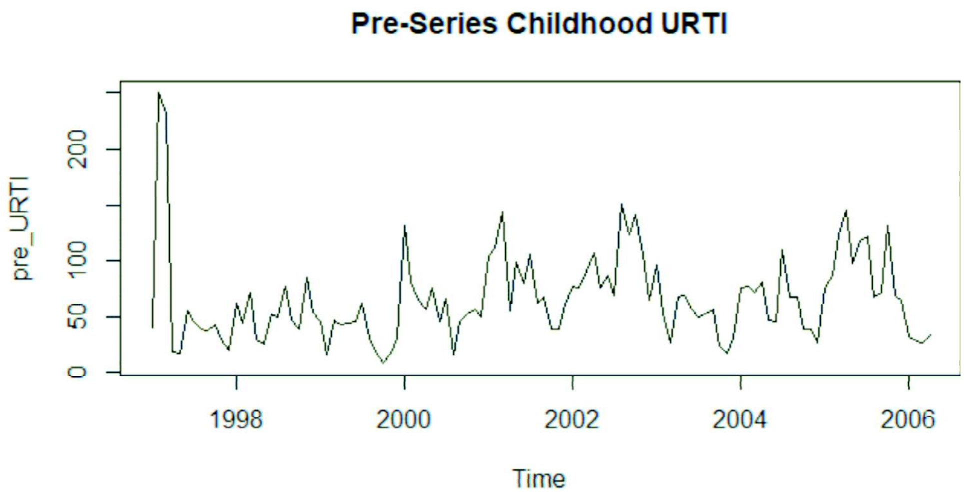

Figure 4: Time Plot of Pre-Series Childhood URTI

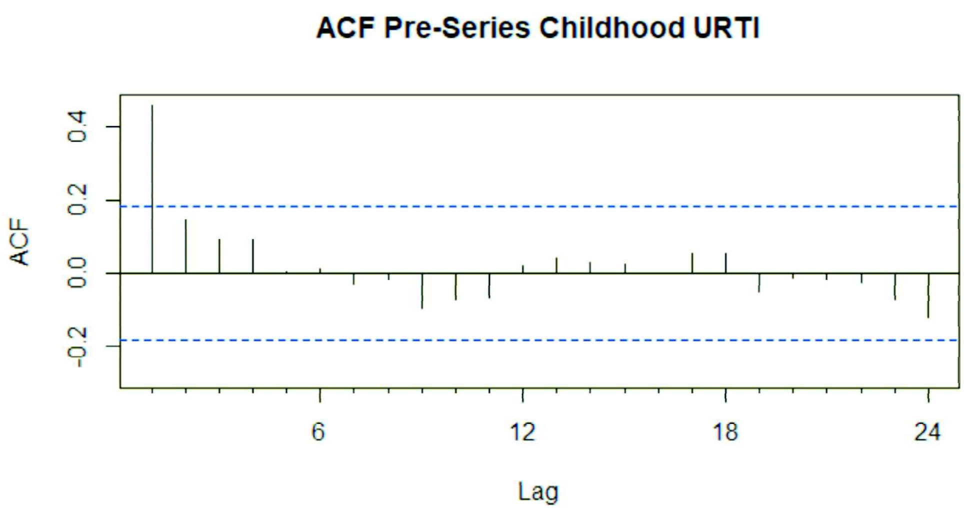

Figure 5: ACF Plot of Pre-Series Childhood URTI

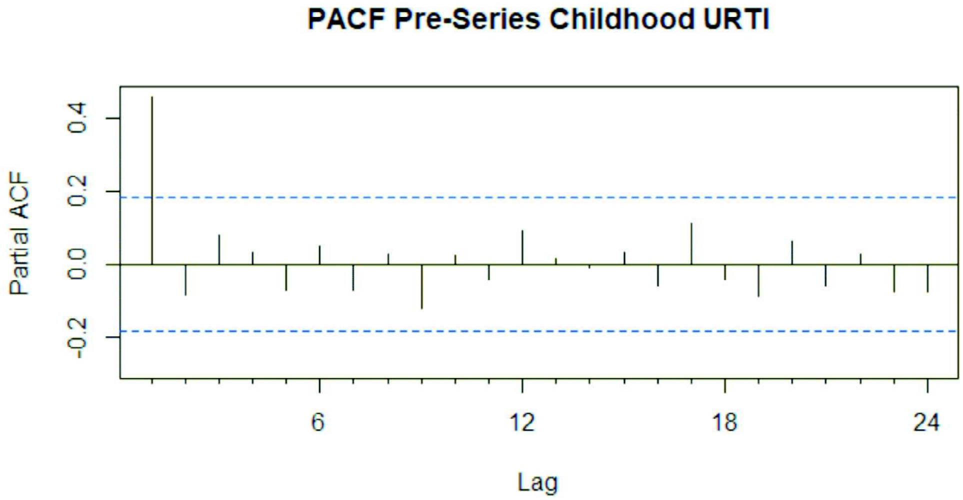

Figure 6: PACF Plot of Pre-Series Childhood URTI

Based on the correlograms in Figures 5 and 6, the ARIMA (1, 0, 0) model is fitted with their statistics summarized in Table 3. The adequacy of the ARIMA (1, 0, 0) model is not in doubt since virtually all its residual correlations are non-significant (*i.e.*, the coefficients of both the ACF and PACF of the residuals are within significance bounds of , Figure 7) and with the least BIC and AIC values of 1131.486 and 1123.331, respectively, Table 4. Hence, the model is statistically significant, appropriate, and adequate for the dataset; see Table 5 (the Ljung-Box test).

Table 3: Parameter Estimation for ARIMA Models

ARIMA(p, d, q)		*Estimate*	*Std. Error*	*Z-value*	*Prob. Value*
(1,0,0)	α_1	0.459070	0.083666	5.4869	4.089e-08 ***
	v	65.436365	6.147618	10.6442	< 2.2e-16 ***
(0,0,1)	β_1	0.455988	0.071633	6.3656	1.945e-10 ***
	μ	65.502834	4.870471	13.4490	< 2.2e-16 ***
(1,0,2)	α_1	-0.872199	0.101421	-8.5998	< 2.2e-16 ***
	β_1	1.447143	0.116408	12.4317	< 2.2e-16 ***
	β_2	0.569964	0.088703	6.4256	1.314e-10 ***
	λ	65.242182	5.237632	12.4564	< 2.2e-16 ***

Table 4: Model Evaluation for ARIMA Models

Model	*BIC*	*AIC*
ARIMA(1, 0, 0)	1131.486	1123.331
ARIMA(0, 0, 1)	1131.794	1123.639
ARIMA(1, 0, 2)	1135.24	1121.648

Table 5: Ljung-Box Test for ARIMA(1, 0, 0) Model Residuals from ARIMA(1, 0, 0)

Q* = 8.8203, df = 21, p-value = 0.9906
Model df: 1. Total lags used: 22

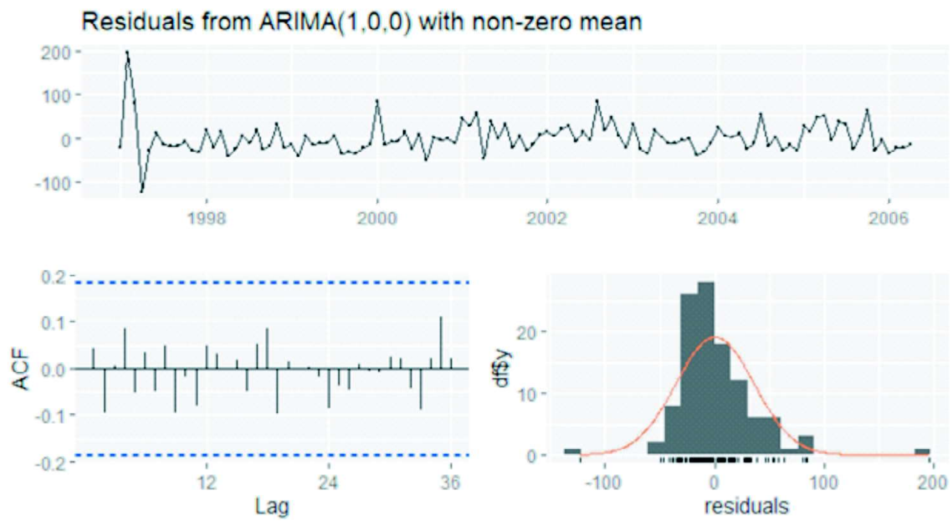

Figure 7: Residual from ARIMA(1, 0, 0) Model

Table 6: Forecast from ARIMA(1, 0, 0) Model

Length	*Date*	*Actual Value*	*Forecast*	*Residuals*
113	May 2006	17	50.54581	34
114	Jun 2006	34	58.60056	25
115	Jul 2006	49	62.29825	13

Table 7: Parameter Estimation for ARIMA(1,0,0)-Intervention Models

Parameter	*Estimate*	*Std. Error*	*Z-value*	*Prob. Value*
α_1	0.618275	0.060265	10.2592	<2e-16 ***
v	89.581634	9.002694	9.9505	<2e-16 ***
ϑ	-22.410200	39.613045	-0.5657	0.5716
d	0			

ARIMA-Intervention Model

The forecasts generated by the ARIMA (1, 0, 0) model were close to the actual value of the post-series (Table 6). The forecasting is done on the first three post-intervention observations to compute the value of the delay parameter. With $d = 0$, it implies that the effect of the intervention was immediate. The impact parameter ϑ, with a value of –22.410200 is non-significant with a p-value of 0.5716. With a nonsignificant impact parameter, it implies that the intervention has no influence.

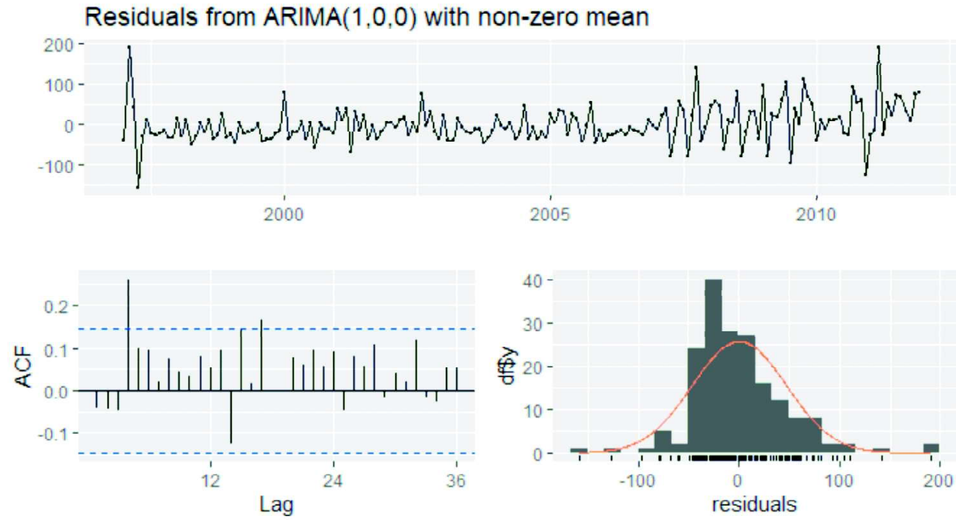

Figure 8: Residual from ARIMA(1, 0, 0)-Intervention Model

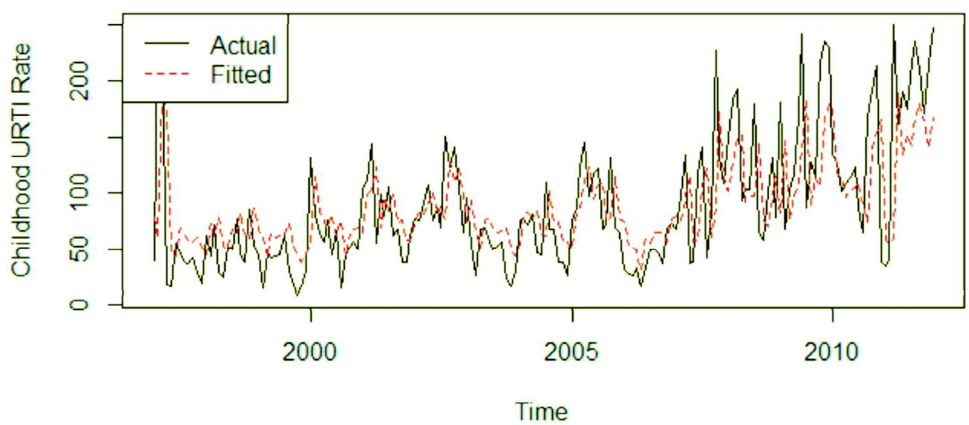

Figure 9: Fitted ARIMA(1, 0, 0)-Intervention Model with Actual Values

The ARIMA-Intervention model is represented mathematically as

$$\int_t = 89.5816 - 22.4102\mho_t^T + \frac{1}{(1-0.6183L)}\eta_t \qquad (11)$$

The model in (11) is statistically significant and adequate for the dataset when diagnosed (see the residual of the fitted model in Figure 8). The goodness of fit of the model is further verified by plotting the fitted model in (11) with the actual values, and it confirms that the model is a good fit since the fitted values mimic the actual values (Figure 9).

CONCLUSION

The data analysis of URTI over 15 years reveals significant insights into the seasonal and long-term trends of this disease. The monthly URTI reported cases indicate a peak incidence during Dry season, particularly from January to March (ranging from 1307 to 1680), which aligns with environmental factors such as Harmattan winds, low humidity, and high temperatures. Whereas, the Wet season, from April to August, witnessed a reduction in cases, likely due to improved air quality and humidity. The yearly trends exhibit a general increase in URTI cases, with a notable drop in 2006, which reflects the call for intervention. The ARIMA-based intervention analysis revealed that a significant intervention in May 2006 did not substantially affect childhood URTI incidence, as the intervention's impact parameter was found to be nonsignificant. Overall, this study highlights the complex dynamics of upper respiratory tract infection incidence in children in Akwa Ibom State, emphasizing the role of seasonal variations and the need for continuous public health measures to mitigate the impact of these infections. However, this study has discovered the generating mechanism and established a framework for determining the future values of childhood URTIs, which will aid government and health experts in establishing optimal system control.

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The authors declare that they have no competing interests.

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