Study of Annual Measles, Forecast, and Trend via Time Series Analysis: Case Study of Nigeria

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Abstract- Measles is an extremely contagious virus that mainly affects youngsters; however, it can strike anyone at any age. In malnourished people, it can cause serious complications, such as pneumonia, and even death of malnourished individuals. Controlling measles requires information on the future forecast or spread. Nigeria continues to represent a substantial portion of global measles mortality due to persistent gaps in information on the future forecast, surveillance, and others. This study examines measles trends in Nigeria from 2012 to 2022 to identify a suitable time series model for forecasting the measles. An ARMA model was applied, and diagnostic tools like ACF, PACF, AIC, and BIC were used for model selection. The selected ARMA (1,1) model demonstrated a good fit for the data, allowing for accurate predictions of measles. These predictions can inform public health strategies and interventions aimed at improving vaccine coverage and enhancing surveillance in Nigeria. Model adequacy was verified using the Ljung-Box test which shows that the model is adequate and well fitted for the forecast. Analysis reveals a cut off of ACF plot after lag 3, and that of PACF after lag 1. These findings can support policy makers in planning effective disease control strategies.

Index Terms- Forcasting, measles, time series, mortality, estimation

I. INTRODUCTION

Measles is one of the deadly diseases globally according to the specification of the World Health Organization (WHO) and it brought greater portion of illness that led to death of children who were not vaccinated at their tender age (World Health Organization, 2020). Measle has a long history in Nigeria, and its transmission is high during the dry season. Ibrahim et al. (2019) mentioned that measles is exceptionally infectious disease mostly affect individuals within the age bracket of 5-6 years, and is preventable at the early stage among children via vaccination. Globally, over 30 million cases have been recorded out of which an annual death of over 1 million were recorded from among African countries (Balogun et al., 2020). Diseases and illnesses like coryza, cough, conjunctivitis, Prodromal fever, and the development of Koplik spots are its hallmarks, and it takes around 10 days to incubate (World Health Organization, 2012). Up to 20 million individuals worldwide contract measles each year; the majority of these cases occur in underdeveloped nations in Asia and Africa (World Health Organization, 2020). From an estimated 873,000 deaths in 1999 to 345,000 in 2005, measles mortality decreased by 60% worldwide (World Health Organization, 2005). According to estimates, the number of measles deaths in 2008 decreased to 164,000, with 77% of the remaining deaths taking place in Southeast Asia (World Health Organizations, 2009).

The illness was eradicated from the Americas by 2016 as a result of improved and widely distributed immunization (United Nations Children's Fund, 2016). According to Ibrahim et al. (2019), measles continues to be a major cause of death and disability in the majority of African nations. The World Health Organization estimates that 134,200 measles deaths occurred in 2015, with a large number of cases occurring in sub-Saharan Africa. According to Masresha et al. (2018), Africa and other developing nations have high case-fatality rates because of early infection, inadequate housing and overcrowding, underlying immune deficiency problems, vitamin A insufficiency, and limited access to healthcare. A third of children in many African nations contracted measles between their first and second years of life prior to the development of vaccinations, and other get it before the age of 5 as pointed out in Masresha et al. (2018).

Approximately 125 million preschool-aged children are vitamin A deficient, putting them at a heightened risk of death, serious illness, and measles-related blindness (World Health Organization, 2018). According to Balogun et al. (2020), measles caused 17% of deaths in children aged 5 to 14 and 22% of fatalities in children under five in Ethiopia in 2000. According to Fatiregun et al. (2014), measles is prevalent in Nigeria, where outbreaks happen often throughout the year. Amshi & Prasad (2023) sought to improve the seasonal autoregressive integrated moving average (SARIMA) model by adding the discrete wavelet transform (DWT). About 73,000 people died from measles infections worldwide in 2014 (World Health Organization, 2014).

The disease has been an endemic illness in Nigeria with repeated spread happening through all months of the year (Fatiregun et al., 2014). Amshi & Prasad (2023) in their research aimed to strengthen the seasonal autoregressive integrated moving average (SARIMA) by incorporating discrete wavelet transform (DWT). To evaluate Nigeria's progress toward measles eradication, Baptiste et al. (2021) conducted a time series trend analysis on the country's vaccine coverage survey from 2008 to 2018. Linda (2004) conducted a study on the monthly cases of infant deaths due to neonatal jaundice in Port Harcourt from the year 1995 to 2004, with the aim of fitting a time series model to analyze the total deaths and forecast ahead. In order to fit a suitable model to the disease, Anthony (2006) conducted a time series analysis on the reported cases of tuberculosis in Abakaliki from 1996 to 2005. The data was analyzed using the Box-Jenkins technique. 94% of measles-related deaths globally occur in 45 countries, including Nigeria (World Health Organization measles fact page, 2012). According to records, the percentage of measles cases resulting from pediatric admissions ranges from 1.3 to 5.1%, and the reported measles fatality rates in Nigeria vary by location, ranging from 1.9% to 12.4% according to Nigeria Centre for Disease Control (NCDC, 2015).

This study uses Nigeria as a case study to examine the measles danger in Sub-Saharan regions of Africa. Data from 2012 to 2022 are specifically examined in order to look into the prevalence of measles in Nigeria. The goal of this study is to fit a suitable model to account for the prevalence of measles in Nigeria. The incidence of measles in Nigeria will be evaluated using a variety of statistical techniques in order to comprehend the disease's historical occurrence and to estimate its future. The government will use this study as a basis for budgetary planning, and residents of the impacted areas will be advised to exercise caution and take the necessary precautions.

Even with the availability of effective vaccines, measles remains a major public health issue in Nigeria and a major contributor to the morbidity and mortality rates worldwide. Measles is highly infectious and its outbreak brings about various illnesses. In undernourished populations and communities with inadequate access to heal of measles can cause catastrophic sequelae such as pneumonia, encephalitis, and even death (World Health Organization, 2021). Given these challenges, robust surveillance and forecasting systems are essential to anticipate future trends and inform targeted intervention efforts.

In order to determine the best forecasting model that might assist policymakers in enhancing vaccination coverage and outbreak preparedness, the current study applies time series analysis to investigate the annual reported cases of measles in Nigeria from 2012 to 2022 (Box et al., 2015). Statistical techniques will be used to evaluate measles cases in Nigeria in order to comprehend the disease's occurrence over time by fitting a suitable model to capture occurrences and forecast utilizing the fitted models. Government fiscal planning will be guided by the findings of this study. It will help to inform people dwelling in the affected areas to be aware of the existence and to take appropriate preventive measures.

II. METHODOLOGY

Data Collection and Discription: Dataset for this project report come from secondary dataset on the yearly reported cases of measles in Nigeria. The data cover the period of 10 years starting from 2012 to 2022. It was got in the website of the Nigeria Centre for Disease Control (NCDC) website https://www.statista.com containing cumulative number of confirmed measles cases in Nigeria. The data on the yearly reported cases of measles in Nigeria were presented in appendices.

Method: In this section, the Box and Jenkins approach and the forecating methods will be discussed. The Box and Jerkins approach introduced by Statisticians George Box-Jenkins and Gwilym (1976) will be employed. Box-Jenkins proposed three stages approach and are:

1. Identification: the identification technique is intended to propose which specific type of model may be relevant to consider.
2. Estimation: applying the identified model to a time series through the likelihood function can provide maximum likelihood estimates of the parameters.
3. Diagnostic checking: diagnostic checks aim to evaluate the adequacy of the model, recommend improvements if needed, and prompt another iterative process or cycle.

Figure 1 displays the iterative stages or approaches in model building as listed in the 3 stages. The first stage is to identify a model; The second step involves estimating the model's parameters, while the third step consists of diagnostic assessment. If the model is evaluated and deemed satisfactory, the researcher will utilize it for forecasting or control purposes. But if the model is discovered not adequate, the whole stages of model building will be repeated starting with the first stage (identification).

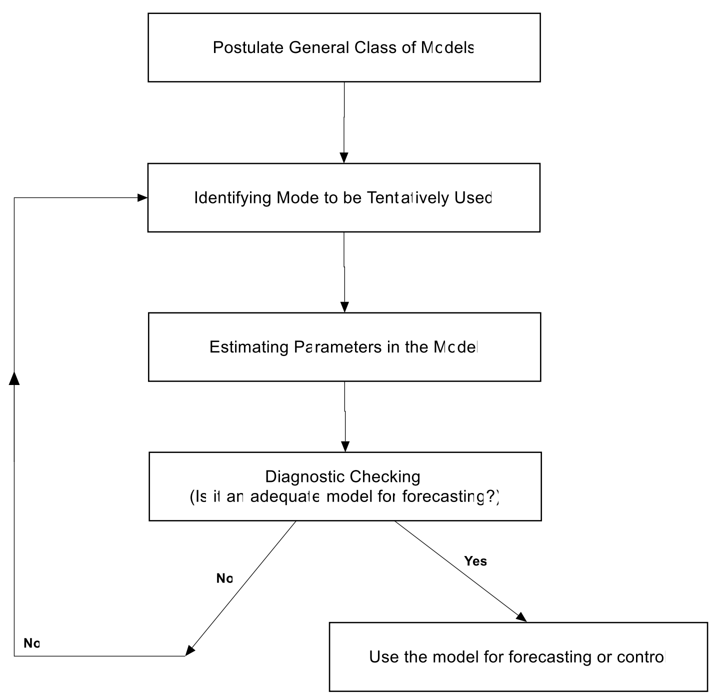

Figure 1. Iterative stages in model building

Forcasting Methods

A. Autoregressive Models: This is a probabilistic model that can be very beneficial in depicting specific practical sequences that take place. In this model, the present value of the process is represented as a finite linear combination of past values of the process and a disturbance, $\boldsymbol{\varepsilon}_t$.

Assuming the results obtained at interval space in time, **t** are $\mathbf{t_1}$, $\mathbf{t_2}$, … by $\mathbf{Z_t, Z_{t-1}, Z_{t-2}}$, … and assume the deviation ($\mathbf{Z_t}$) from the mean, μ are $\mathbf{Z_t, Z_{t-1}, Z_{t-2}}$, …

$\mathbf{Z_t = Z_t - \mu}$. Then sxx

$$\mathbf{Z_t = \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \varphi_p Z_{t-p} + \varepsilon_t} \tag{1}$$

is Autoregressive process (AR) of order p.

B. Moving Average Models: In time series analysis, the moving average model (MA) is a widely used method for modeling univariate time series. It indicates that the result is linearly influenced by the present and several earlier values of a stochastic (partially predictable) factor. It is also a method used to assess data points by generating a sequence of averages from various subsets of the complete data set. It is shown in (2).

$$\mathbf{X_t = \varepsilon_t \ldots \theta_1 \varepsilon_{t-1} \ldots \theta_2 \varepsilon_{t-2} \ldots \theta q \ \varepsilon_{t-q}} \qquad (2)$$

It can be transformed to include a backward equation:

$$\mathbf{X_t = \varepsilon_t \ldots \theta_1 B \, \varepsilon_t \ldots \theta_2 B^2 \varepsilon_t \ldots \theta q \, B^q \varepsilon_t}$$

$$\mathbf{X_t = (1\text{-}\theta_1 B\varepsilon_t \ldots \theta_2 B^2 \varepsilon_t \ldots \theta q \, B^q) \, \varepsilon_t} \qquad (3)$$

$\mathbf{X_t = \theta(B) \, \varepsilon_t}$; where $\mathbf{\theta(B) = 1\text{-} \, \theta_1 B\varepsilon_t \ldots \ldots \theta_2 B^2 \varepsilon_t \ldots \theta q \, B^q}$ and is referred to as the characteristic polynomial of the MA process of order q. This process is viewed as the output, $\mathbf{X_t}$, from a linear filter with transfer function $\mathbf{\theta(B)}$, which results from the output of white noise, $\boldsymbol{\varepsilon_t}$.

C. Autoregressive Moving Average (ARMA): ARMA is a forecasting model that combines autoregression (AR) analysis and moving average (MA) techniques on well-behaved time series data. In ARMA, it is assumed that the data are stationary, and when variations occur, they do so consistently around a specific time. It is characterized in the following way:

$$\mathbf{Z_t = \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots + \varphi_p Z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}} \qquad (4)$$

where,

$\boldsymbol{\varphi}$'s = parameters to be estimated in AR process

$\boldsymbol{\theta}$'s = parameters to be estimated in MA process

$\mathbf{Z}$'s = series observation

$\boldsymbol{\varepsilon_t}$'s = residuals

The B in (5) and (6) represent the backward operator introduced by Box and Jenkins with a target of varying the time $_t$ to $_{t-1}$ etc. Therefore,

$$\mathbf{BZ_t = Z_{t-1}} \qquad (5)$$

$$\mathbf{B^2 Z_t = Z_{t-2}} \qquad (6)$$

The above equations are known as the backward shift operator notation.

III DATA ANALYSIS AND RESULTS

A. Graphing the Observation

The initial step in evaluating time series data is to graph the observations over various time intervals. The yearly measles case data gathered from the Nigeria Centre for Disease Control (NCDC) is plotted against the respective years from 2012 to 2021.

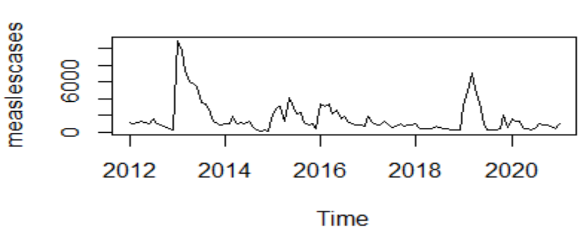

Figure 2: Time plot for the measles case

Figure 2 showed that the number of measles cases decreased between 2015 and 2018, then skyrocketed in 2019. Nonetheless, there is a discernible decline from 2020 to 2021. Generally speaking, the number of measles cases has been declining during the research period.

B. Stationarity Test

This research employs the Augmented Dickey-Fuller test (ADF) to examine stationarity and to check for a unit root's existence. A unit root assists in recognizing certain characteristics of a series, and when a unit root exists in a series, it is deemed stationary; if not, it is classified as non-stationary. The presence of a unit root will be assessed using the Augmented Dickey-Fuller (ADF) test.

$$\mathbf{ADF_t = \frac{\emptyset}{SE(\emptyset)}} \qquad (7)$$

where,

Ø is the least square estimate of the parameters $\frac{\emptyset}{\mathbf{SE(\emptyset)}}$

$\mathbf{SE}(\emptyset)$ is the standard error of (Ø)

Hence, we shall confirm how stationary the data is via Augmented Dickey-Fuller (ADF), and the test hypothesis is given below;

Hypothesis:

H_0: claim of presence of unit root

H_1: no unit root exists

At the significant value of 0.05 (i.e., α = 0.05)

Test Statistics: $\mathbf{ADF_t = \frac{\emptyset}{SE(\emptyset)}}$

Rule of Decision: Discard the null hypothesis when the p-value is less than the α-value;

Table 1: Augmented Dickey-Fuller (ADF) Test

ADF	Test statistic	p-value
Yearly reported cases	-4.5204	0.01

Conclusion: Given that the p-value of 0.01 is below α of 0.05, we reject the null hypothesis and conclude there is no unit root present which implies that the yearly reported cases of measles is stationary at α = 0.05.

IV MODEL'S IDENTIFYING

As mentioned earlier, the model can be determined using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The actions of autocorrelation and partial autocorrelation functions are analyzed thoroughly. The table below displays the theoretical patterns of ACF and PACF.

Model	ACF	PACF
AR (p)	AR tail-off to zero/decay	Here, it cut-off across lag (p)
MA (q)	MA cut-off across lag (q)	Here, it tail-off to 0 and decays
ARMA (p, q)	ARMA cut-off across lag(p)	Here, it cut-off across lag (q)

The illustrations below demonstrate the identification of autoregressive (AR) and moving average (MA) models through the use of the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

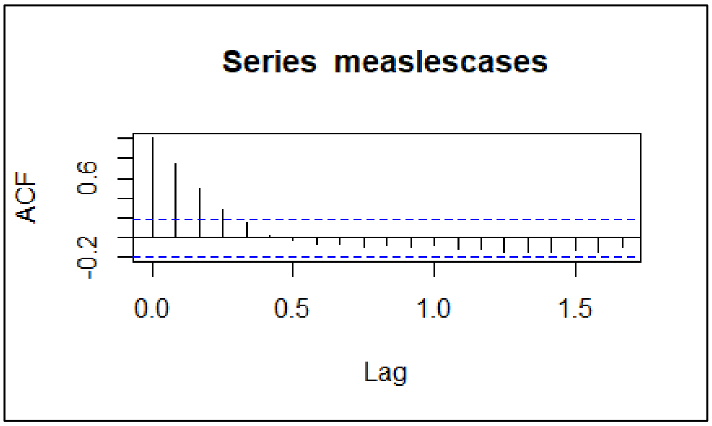

Figure 3: Graph of the Autocorrelation Function

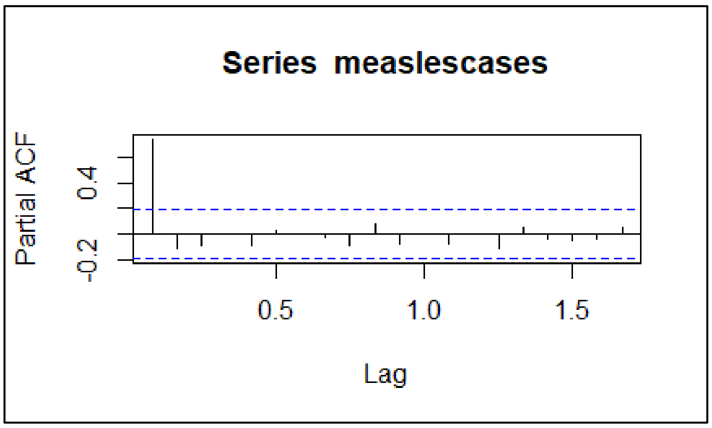

Figure 4: Graph of the PartialAutocorrelation Function

The ACF and PACF will assist in determining the appropriate time series model. The data indicates that the ACF truncates at lag 3, while the PACF truncates at lag 1 without differencing the original dataset, hence the plot implies that an ARMA (1,3) model would suit the time series well. To determine the optimal ARMA model, a selection process will be conducted. The method consists of evaluating the models listed in the table below, with the lowest Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). In statistics, the Bayesian Information Criterion and Akaike Information Criterion serve as criteria for selecting models from a limited set of models; models exhibiting lower BIC and AIC values are typically favored.

Table 3: Model Selection of Various ARMA

Models	BIC	AIC
ARMA(1,0)	2088.64	2071.25
ARMA(1,1)	2082.558	2070.31
ARMA(1,2)	2086.128	2072.15
ARMA(1,3)	2090.882	2074.11
ARMA(2,0)	2083.09	2072.91
ARMA(2,1)	2086.081	2072.10
ARMA(2,3)	2090.322	2071.75
ARMA(3,1)	2085.196	2078.42
ARMA(3,2)	2090.05	2072.48
ARMA(3,3)	2094.278	2071.91

From table 3 above, ARMA (1,1,) was selected as the best model because it has minimum BIC and AIC. Thus,

$$\mathbf{x_t = \varphi_1 x_{t-1} - \theta_1 \varepsilon_{t-1} + \varepsilon_t} \quad (8)$$

will be adopted as the suitable model.
where,
$\mathbf{x_t}$ is the original series at time, t
$\boldsymbol{\varphi}$ is the autoregressive parameter to be estimated
$\boldsymbol{\theta}$ is the moving average parameter to be estimated
$\boldsymbol{\varepsilon_t}$ is the white noise error term at time, t

C. Estimation of Parameters in the Model

After identifying the time series model (annual measles cases) through the ACF and PACF of the time series table, along with analyzing the model summary table above, it is now sufficient to estimate the parameters of the identified model. Thus, by analyzing $\mathbf{x_t = \varphi_1 x_{t-1} - \theta_1 \varepsilon_{t-1} + \varepsilon_t}$, the parameters $\boldsymbol{\varphi}$ and $\boldsymbol{\theta}$ will be estimated using the least squares approach. The least squares estimation for an ARMA (1,1) process is provided as:

Table 4: ARMA (1,1) Model Parameters Estimation

Model parameters	Estimate	SE	t	P-value
Constant	1502395	176.29423	2.557	0.0105
$\boldsymbol{\varphi_1}$	0.70373	0.08168	8.615	0.2898
$\boldsymbol{\theta_1}$	0.11203	0.10584	1.059	0.0000

$$\mathbf{x_t = 1502395 + 0.70373\, x_{t-1} - 0.11203\, \varepsilon_{t-1} + \varepsilon_t} \quad (9)$$

D. Diagnostic Checking of the ARMA (1,1) Model

Here, Ljung Box Q Statistic (Ljung and Box,1978) was employed to check for the model adequacy. The adequacy of the identified model will be assessed by examining the residuals from the fitted model. The Ljung Box test determines if the residuals are independently identically distributed (i.e. white noise) by testing for absence of serial autocorrelation.
The Ljung-Box Statistic is defined as;

$$\mathbf{Q(m) = n(n+2)\sum_{i=1}^{m} \frac{\rho_i}{n-i}} \quad (10)$$

where,
n = observations
ρ_i = autocorrelation coefficient at lag $_i$ of the residual series
Q = Ljung-Box test statistic for assessing the model's adequacy. m represents the time delay.
Hence, adequacy of the model shall be confirmed given the test of hypothesis below;

Hypothesis:
H_0: The model is adequate
H_1: The model is not adequate
$\alpha = 0.05$
Test statistic: $\mathbf{Q(m) = n(n+2)\sum_{i=1}^{m} \frac{\rho_i}{n-i}}$
Decision Rule: Discard the null hypothesis if the p-value is below α; if not, accept it.

E. Computation of ACF and PACF Plots

Table 5: Ljung-Box Test

Box- Ljung Test	T-Statistic	P-value
ARMA (1,1)	6.3747	0.896

Conclusion: as the p-value = 0.896 is not below α = 0.05, we fail to reject the null hypothesis (accept the null hypothesis) and determine that the model is sufficient at α = 0.05.

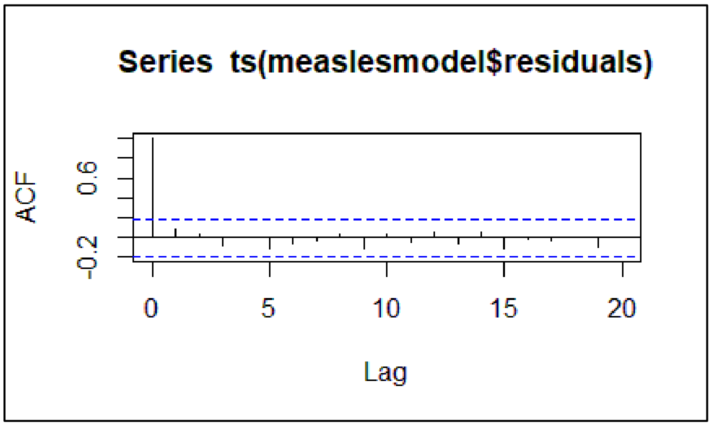

Figure 5: Graph of the Autocorrelation R

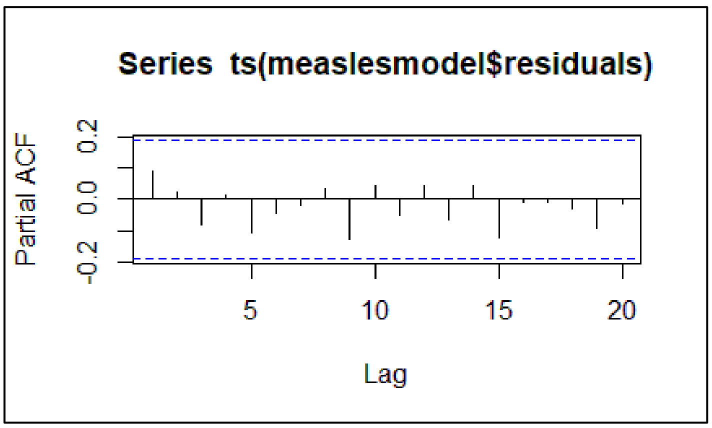

Figure 6: Plot of Partial Autocorrelation

It was observed from Figures 5 and 6 that the observations in time series data fell within 95% confidence interval. This indicates that the model is sufficient and can be utilized for predictions.

F. Forecasting

Since the adequacy of the model has been established by diagnostic checking, the model will now be used for forecasting. Like clustering, there is existence of patition according to forecast years and months (Ohanuba 2023).

Table 6: Forecast for 5 Years (Jan 2022- 2027)

Monthly	Forecast	LCL (95)	UCL (95)
Jan 2022	1103.559	-1432.400	3639.518
Feb 2022	1240.126	-1908.611	3639.518
March 2022	1340.636	-2094.679	4775.951
April 2022	1414.608	-2166.372	4995.589
May 2022	1469.051	-2188.409	5126.510
June 2022	1509.118	-2189.106	5207.343
July 2022	1538.608	-2181.512	5258.727
August 2022	1560.311	-2171.614	5292.236
September 2022	1620.809	-2125.020	5366.637
October 2022	1620.809	-2125.020	5366.637
November 2022	1620.809	-2125.020	5366.637
December 2022	1620.809	-2125.020	5366.637
January 2023	1620.809	-2125.020	5366.637
February2023	1620.809	-2125.020	5366.637
March 2023	1620.809	-2125.020	5366.637
April 2023	1620.809	-2125.020	5366.637
May 2023	1620.809	-2125.020	5366.637
June 2023	1620.809	-2125.020	5366.637
July 2023	1620.809	-2125.020	5366.637
August 2023	1620.809	-2125.020	5366.637
September 2023	1620.800	-2125.028	5366.629
October 2023	1620.804	-2125.024	5366.633
November 2023	1620.803	-2125.026	5366.629
December 2023	1620.801	-2125.031	5366.631
January 2024	1620.808	-2125.021	5366.636
February 2024	1620.808	-2125.021	5366.636
March 2024	1620.808	-2125.021	5366.636
April 2024	1620.808	-2125.021	5366.636
May 2024	1620.808	-2125.021	5366.636
June 2024	1620.808	-2125.021	5366.636
July 2024	1620.808	-2125.021	5366.636
August 2024	1620.798	-2125.48	5366.626
September 2024	1620.793	-2125.052	5366.622
October 2024	1620.788	-2125.067	5366.617
November 2024	1620.780	-2125.074	5366.609
December 2024	1620.777	-2125.082	5366.600
January 2025	1620.770	-2125.087	5366.599
February 2025	1620.756	-2125.091	5366.585
March 2025	1620.738	-2125.103	5366.566
April 2025	1620.712	-2125.111	5366.541
May 2025	1620.677	-2125.120	5366.506
June 2025	1620.630	-2125.156	5366.459
July 2025	1620.566	-2125.189	5366.395
August 2025	1620.479	-2125.194	5366.307
September 2025	1620.361	-2125.212	5366.189
October 2025	1620.200	-2125.225	5366.027
November 2025	1619.981	-2125.845	5365.807
December 2025	1619.684	-2126.140	5365.508
January 2026	1619.281	-2126.539	5365.101
February 2026	1618.733	-2127.080	5364.545
March 2026	1617.988	-2127.811	5363.787
April 2026	1616.976	-2128.797	5362.749
May 2026	1615.601	-2130.125	5361.327
June 2026	1613.733	-2131.906	5359.372
July 2026	1611.194	-2134.284	5356.673
August 2026	1607.745	-2137.436	5352.927
September 2026	1603.059	-2141.575	5347.693
October 2026	1196.691	-2146.931	3639.518
November 2026	1103.311	-1432.400	3639.518
December 2026	1100.751	-1492.400	3639.498
January 2027	1080.619	-1332.400	3659.510

IV CONCLUSION

This research work has provided a statistical analysis of cases of measles obtained in Nigeria from period of January 2012 and December 2022. ARMA model was fitted on the yearly cases of measles in Nigeria. The ACF and PACF plots assist in identifying the time series model, and it was noted that ARMA (1,1) was selected as the optimal model due to its lowest BIC and AIC values. The Ljung-Box test was performed to assess the model's suitability, revealing that the residuals were converted into white noise, indicating that the model is appropriate and can be utilized for forecasting. The findings of this research showed a decrease in the number of measles cases throughout the examined period. A reduction in the number of measles cases was noted from 2015-2018 to 2019-2022. Nevertheless, a significant rise was noted in 2013. A decline in measles cases is anticipated from 2022 to 2027 according to the projected time graph.

RECOMMENDATION

The result of this research work has shown that not much funds is needed for measles as the prevention measures put in place by world health organization has proven to be effective. However, additional research on the pattern and distribution of the diseases throughout geopolitical areas is necessary to identify which region is more vulnerable and what actions are needed to control the trend.

APPENDIX

M /Yr	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Jan	1123	10906	1002	2092	3352	1823	939	2983	1618	918	937
Feb	989	9768	1023	2912	3096	1190	412	4905	1301	934	412
Mar	1093	7432	1811	3095	3281	874	415	7120	1209	681	495
April	1209	6041	1041	1208	2098	856	320	5229	398	405	346
May	1100	5723	1061	4054	2632	1210	390	3536	423	508	397
June	978	5500	904	3287	1564	783	650	971	218	632	659
July	1554	3432	1244	2213	1876	549	560	250	580	476	568
Aug	959	3321	463	2254	1112	676	312	274	932	651	401
Sept	856	2806	304	1181	972	952	423	187	851	401	506
Oct	575	1273	150	786	812	710	251	375	764	471	302
Nov	413	927	208	907	890	803	201	2064	610	329	222
Dec	212	763	132	432	684	762	194	546	412	312	211

Reported cases of Measles between 2012 and 2022

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