International Journal of Data Science and Analysis
2024, Vol. 10, No. 5, pp. 100-108
https://doi.org/10.11648/j.ijdsa.20241005.12

Research Article,

Modelling Seasonal Variation and Lassa Fever Outbreak in Nigeria: A Predictive Approach

Adesola Musa[1,*], Kazeem Osuolale[1], Dayo Lawal[1], Abideen Salako[2], Fewajesuyan Aponinuola[3], Wakilat Tijani[1], Abass Adigun[4], Babatunde Salako[2]

[1]Grant (Biostatistics Subunit), Nigerian Institute of Medical Research, Lagos, Nigeria
[2]Department of Clinical Sciences, Nigerian Institute of Medical Research, Lagos, Nigeria
[3]Internal Medicine Department, Federal Medical Center, Owo, Nigeria
[4]Information and Communications Technology Department, National Centre for Remote Sensing, Nabatum, Nigeria

Abstract

Background: Lassa fever, a severe viral hemorrhagic fever caused by the Lassa virus, is a significant public health concern in West Africa, particularly in Nigeria. First identified in the 1950s, Lassa fever has been a persistent threat, causing outbreaks annually. This study investigates the temporal patterns and trends of Lassa fever outbreaks in Nigeria between 2017 and 2023, leveraging a comprehensive dataset from the Nigerian Centre for Disease Control (NCDC). *Objective*: The goal of this study is to analyze the seasonal variations and predict future occurrences of Lassa fever outbreaks in Nigeria. By employing the Box-Jenkins time series analysis and geo-spatial analysis, we aim to: Identify temporal patterns by Examining monthly and annual trends in Lassa fever case numbers, Forecast future outbreaks by utilizing an ARIMA model to predict future incidence rates and inform public health strategies by providing evidence-based recommendations to improve Lassa fever prevention and control efforts. *Methods*: This study utilized a secondary dataset comprising over 60 data points collected from the NCDC portal between 2017 and 2023. The Box-Jenkins time series analysis, specifically the ARIMA model, was employed to analyze the temporal patterns and forecast future trends. The model's adequacy was assessed using the Ljung-Box test. Additionally, geo-spatial analysis was conducted to visualize the spatial distribution of Lassa fever cases. *Results:* The analysis revealed distinct seasonal patterns in Lassa fever incidence, influenced by Nigeria's climatic and environmental conditions. Monthly fluctuations in confirmed cases were observed, with peak periods aligning with specific seasons. The ARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model demonstrated a strong fit to the data, providing reliable forecasts for future outbreaks. *Conclusion:* This study underscores the importance of strengthening surveillance systems for early detection and rapid response to Lassa fever outbreaks, particularly during peak seasons. Implementing effective rodent control measures, promoting good hygiene practices, and improving environmental sanitation are crucial for reducing the risk of Lassa fever transmission. Furthermore, enhancing collaboration between government agencies, healthcare providers, and research institutions is essential for optimizing Lassa fever prevention and control efforts.

Keywords

Lassa Fever, Time Series, ARIMA, Box-Jenkins, Temporal Patterns, Seasonal Variation, Forecasting

*Corresponding author: zaidatmusa@gmail.com (Adesola Musa)

Received: 14 October 2024; **Accepted:** 4 November 2024; **Published:** 29 November 2024

Copyright: © The Author(s), 2024. Published by Science Publishing Group. This is an **Open Access** article, distributed under the terms of the Creative Commons Attribution 4.0 License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.

1. Introduction

Arenaviruses are a type of RNA virus with a unique genetic structure. They are classified as bi-segmented ambience RNA viruses and are members of the Arenaviridae family [1]. At least eight arenaviruses are known to cause human disease and these viruses have been responsible for significant outbreaks in different parts of the world [2]. Disease caused by arenaviruses can vary in severity from relatively mild, to severe, leading to hemorrhagic fevers and other serious symptoms [3]. Lassa fever, a viral hemorrhagic disease caused by the Lassa virus (LASV), belonging to the Arenaviridae family remains a major problem of public health concern in Nigeria and other West African countries. It was first detected in 1969 in the city of Lassa, Borno State, Nigeria, during an outbreak that claimed the lives of two missionary nurses [4, 6]. Since then, the disease has been recognized as an endemic threat in several West African countries, including Nigeria, Sierra Leone, Liberia, and Guinea. The primary host of Lassa virus is the multimammate rat (Mastomys natalensis), which carries the virus asymptomatically and sheds it in urine and feces. Human infection usually occurs through contact with contaminated surfaces or ingestion of food contaminated with the infected rodent feces or urine or the rodents themselves. Human-to-human transmission via contact exposure to the virus from the blood or bodily fluids of an infected person is also commonly seen [4]. Laboratory transmission can also occur, particularly in health care settings in the absence of adequate infection prevention [5]. The clinical manifestations of Lassa virus infection can vary significantly among patients. Commonly reported signs and symptoms tend to emerge within a window of one to three weeks following exposure to the virus. The incubation period and time to symptom onset vary, reflecting the diverse ways the disease manifests in different individuals [7]. About 80% of people infected have mild or no symptoms, while 20% of those infected develop more serious symptoms, such as bleeding (in the fingers, eyes or nose), difficulty breathing and often vomiting, facial swelling, chest pain, back pain and stomach pain [4, 8].

Characterized by its seasonal outbreaks, Lassa fever poses a serious threat to human health, with the potential for massive infection and high mortality if not managed effectively. Understanding the dynamics of Lassa fever outbreaks, especially with respect to seasonality, is important to design targeted intervention strategies and improve healthcare preparedness in endemic regions. In recent years, the use of predictive modeling techniques has also emerged as an important tool to predict and understand the periodic patterns of Lassa fever outbreaks in Nigeria [9]. This study provides an overview of the observed seasonal variation in the incidence of Lassa fever, examines the factors contributing to this variability, and generates a relatively accurate prediction of Lassa fever outbreaks using data collected by the Nigeria Centre for Disease Control (NCDC) from weekly situational reports from NCDC between 2017 and 2023.

2. Materials and Methods

2.1. Study Design and Data Sources

This study employed a retrospective cohort analysis of weekly epidemiological situation reports on suspected, confirmed, and probable cases, as well as case facility ratio related to Lassa fever outbreaks. The data were sourced from the publicly accessible Nigeria Centre for Disease Control (NCDC) website (https://ncdc.gov.ng/diseases/ sitreps). Over 60 data points were extracted, covering a seven-year period from 2017 to 2023. The data were compiled in Microsoft Excel, cleaned, and validated for subsequent analysis.

2.2. Time-Series Analysis and Forecasting

Time series analysis and forecasting were conducted using the Auto-Regressive Integrated Moving Average (ARIMA) model. The steps involved included: first, plotting the data to visually inspect trends, seasonality, and potential outliers. Next, the data was tested for stationarity using the Augmented Dickey-Fuller (ADF) test, as ARIMA requires stationary data. Following this, an appropriate ARIMA model was identified by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, which helped determine the autoregressive (p), differencing (d), and moving average (q) components. The data was then fitted using maximum likelihood estimation and the Akaike Information Criterion (AIC) was employed to assess the relative goodness-of-fit of the model. After fitting the model, diagnostic checks were performed, including an analysis of the residuals to ensure they resembled white noise, indicating a good fit. The validated ARIMA model was subsequently used to forecast future Lassa fever outbreaks, with confidence intervals provided to account for predictive uncertainty. To enhance model accuracy, a Seasonal ARIMA (SARIMA) model was used due to the strong seasonal patterns. The model's predictions were then compared against historical outbreak data to evaluate performance metrics, such as the mean absolute error (MAE). A sensitivity analysis was conducted to understand how variations in model parameters impacted forecast accuracy. Finally, the model can be used to generate both short-term and long-term outbreak predictions, supporting public health preparedness and resource allocation.

3. Results

The observed spatial and temporal patterns highlight the complex nature of Lassa fever transmission and emphasize the need for targeted interventions in high-risk areas. (Figure 1).

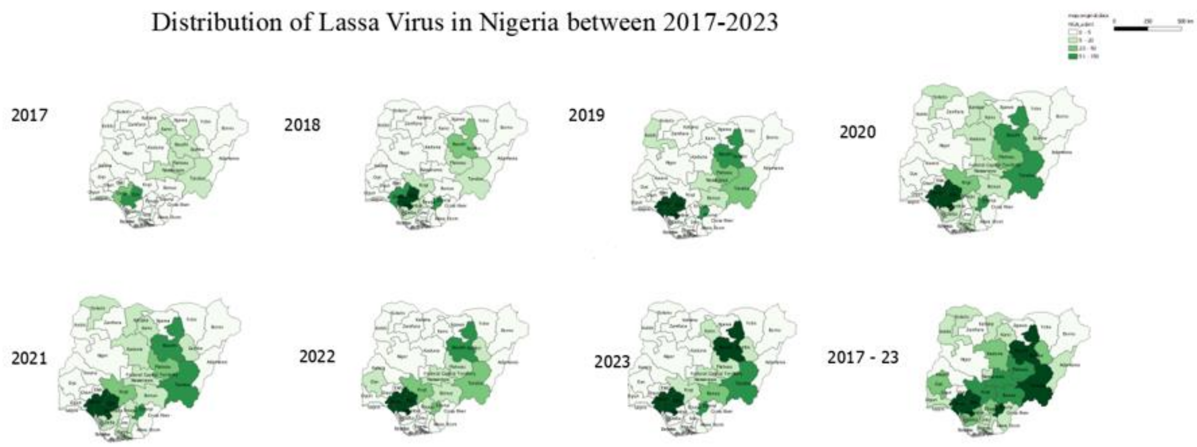

Figure 1. *Temporal distribution of Lassa fever incidence in Nigeria, 2017– 2023.*

3.1. Time Series Analysis and Plot

The seasonal variation of Lassa virus in Nigeria reveals distinct patterns shaped by the country's weather and environmental conditions. Data from 2017 to 2023 show fluctuations in confirmed Lassa fever cases across different months, indicating clear seasonal trends in disease incidence. (Figure 2).

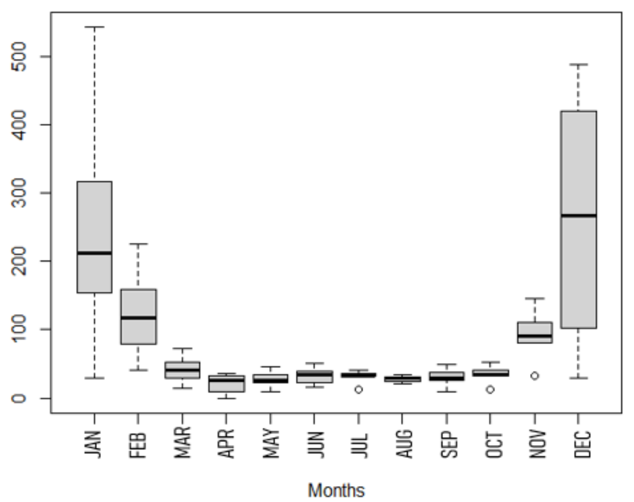

Figure 2. *Boxplot of Monthly Lassa Fever Variability from Jan-Dec (2017 - 2023).*

Four basic steps were taken in this study to analyze time series data effectively:

3.1.1. Step 1

The initial step in time series analysis involves constructing a time plot of the series. This plot displays observations on the y-axis against equally spaced time intervals on the x-axis. It is used to evaluate patterns and behaviors in the data over time. (Figure 3).

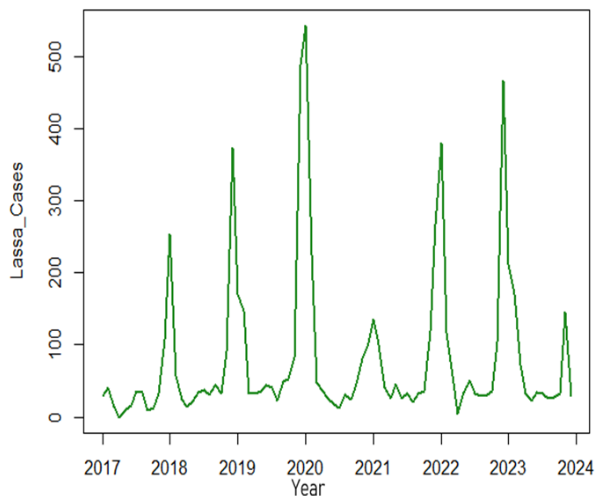

Figure 3. *Time Series Plot of Lassa Fever Outbreak in Nigeria from 2017 -2023.*

3.1.2. Step 2

The time series decomposition involves breaking down the observed data into four components: observed, trend, seasonal, and random. The observed panel shows the Lassa fever confirmed cases over time, capturing all variations. The trend component reveals the long-term progression with noticeable increases and decreases such as those around 2020 which may correlate with the COVID-19 pandemic. The seasonal component reveals recurring patterns each year with consistent cycles, peaks and troughs. The random component represents the irregular variations or noise remaining after removing the trend and seasonal effects. This decomposition helps identify distinct structures within the time series.

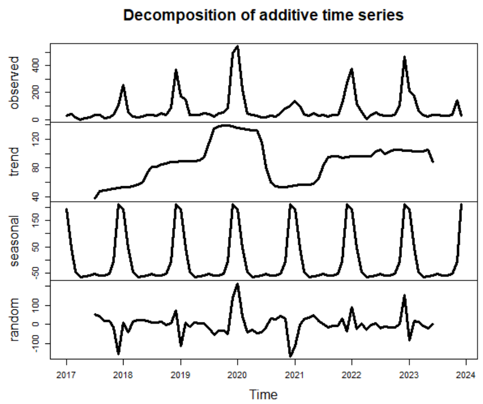

Figure 4. *Decomposition of Lassa Fever Outbreak in Nigeria.*

3.1.3. Step 3

The first difference of the series is calculated by finding the change between each consecutive observation. This process transforms the series into differences between time points, which helps remove trends and stabilize the mean, making the data more stationary. By focusing on changes rather than absolute values, first differencing can reveal patterns and reduce the impact of non-stationarity. For each time point t, the first difference Δy_t is calculated as (Figure 5)

$$\Delta y_t = y_t - y_{t-1}$$

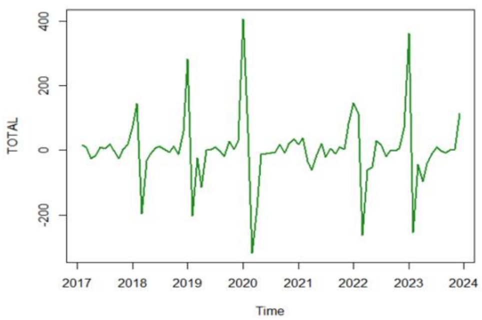

Figure 5. *Time Series Plot of the First Difference of Lasa Fever Data.*

The second differencing of a time series involves calculating the difference of the already differenced data, essentially focusing on the change between consecutive differences. This technique is useful for eliminating both linear trends and certain types of seasonality, particularly when the first differencing does not sufficiently stabilize the series. By applying the second difference, we can highlight the acceleration or deceleration in the data, revealing subtle patterns or cycles that may not have been apparent after the first differencing. For each time point t, the second difference $\Delta^2 y_t$ *is* calculated as: (Figure 6).

$$\Delta^2 y_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$$

$$\Delta^2 y_t = y_t - 2y_{t-1} + y_{t-2}$$

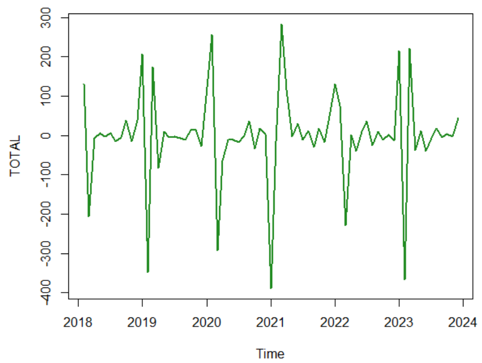

Figure 6. *Time Series Plot of the Second Difference of Lasa Fever Data.*

The Augmented Dickey-Fuller (ADF) test for stationarity was conducted. The test showed that the unit root test is significant ($p<0.05$). The series is a differenced stationary process of order one {I(1)}. (Table 1)

Table 1. *Stationarity tests of Lassa series after first difference.*

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
z.lag.1	-1.1966	0.1566	-7.642	4.33E-11***
z.diff.lag	0.2031	0.111	1.83	0.071

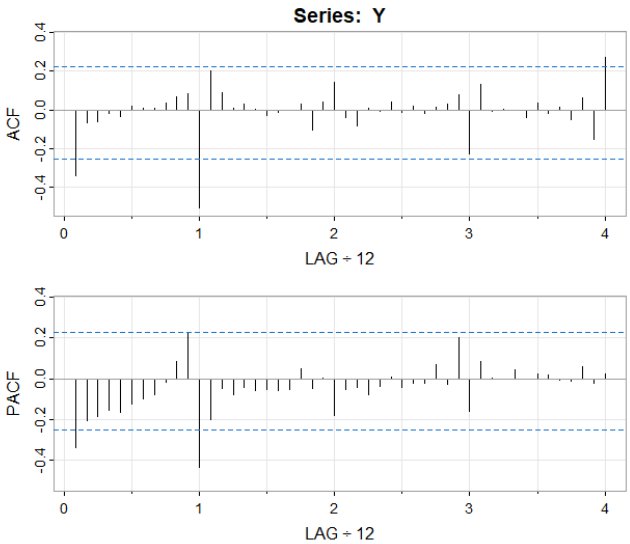

Figure 7. *ACF and PACF of Lassa Fever Outbreak (2017-2023).*

3.1.4. Step 4.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots shows significant spikes at lag

1, suggesting potential configurations for an ARIMA model. Both plots show abrupt cutoffs at lag 1, indicating that AR and MA terms of order 1 (p = 1, q = 1) may be appropriate. Seasonal components also exhibit significant spikes at the seasonal lag (12), showing possible seasonal ARIMA models with seasonal terms P and Q equal to 1. Consequently, four potential ARIMA models were considered: ARIMA (1, 1, 0)(1, 1, 0)12, ARIMA (1, 1, 0)(0, 1, 1)12, ARIMA (0, 1, 1)(1, 1, 0)12, and ARIMA (0, 1, 1)(0, 1, 1)12. The optimal model among these will be selected based on the Akaike Information Criterion (AIC). (Figure 7)

3.2. Akaike Information Criterion (AIC) Estimation

The objective of the identification phase is not to rigidly select a single correct model but to narrow down the choice of possible models that will subsequently be subjected to further examination. Consequently, we select tentative models for different values of (p, d, q) and find estimates of the model parameters. Estimated model with the least Akaike Information Criterion (AIC) will be preferred. The results presented in Table 2 show the selection criteria for different ARIMA models, with ARIMA (0, 1, 1)(0, 1, 1)$_{12}$ having the lowest AIC value of 834.344, indicating it is the best model among the four considered.

Table 2. *Selection Criteria.*

S/N	(p, d, q) (P, D, Q)$_{12}$	AIC
1	(1, 1, 0)(1, 1, 0)$_{12}$	850.052
2	(1, 1, 0)(0, 1, 1)$_{12}$	837.037
3	(0, 1, 1)(1, 1, 0)$_{12}$	846.399
4	(0, 1, 1)(0, 1, 1)$_{12}$	834.344***

The diagnostic plots for the ARIMA model in Figure 8 show that the standardized residuals are homoscedastic, displaying a consistent spread around zero which suggests constant variance. The ACF plot reveals that all autocorrelation spikes fall within the 95% confidence bounds, indicating no significant autocorrelation and confirming the stationarity of the residuals. Additionally, the p-values for the Ljung-Box test are above the significance level, supporting the null hypothesis of no autocorrelation in the residuals. These findings confirm that the residuals are white noise, demonstrating that the ARIMA model is well-specified and suitable for forecasting future values of the time series. (figure 8)

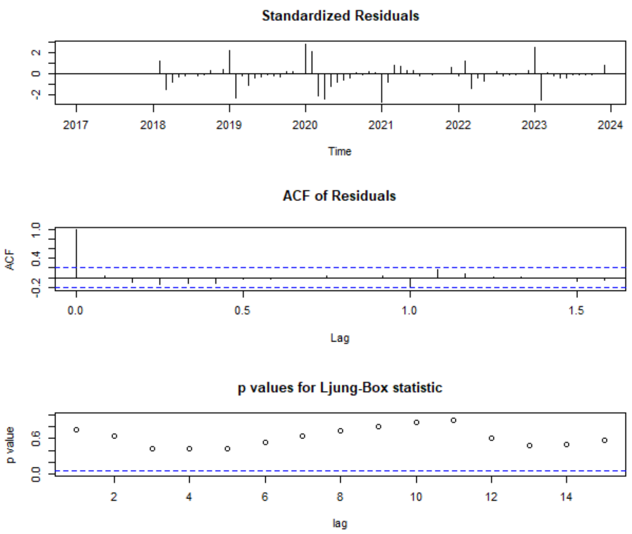

Figure 8. *Plots of Time Series Diagnostics for the ARIMA (0, 1, 1) (0, 1, 1)$_{12}$ Model.*

3.3. Forecasting

Figure 9 presents the forecasted values for the Lassa fever confirmed case rate over a six-year period. The result shows an upward trend. The six-year forecast, represented by dotted lines in Figure 9 confirms this increasing trend. (Figure 9)

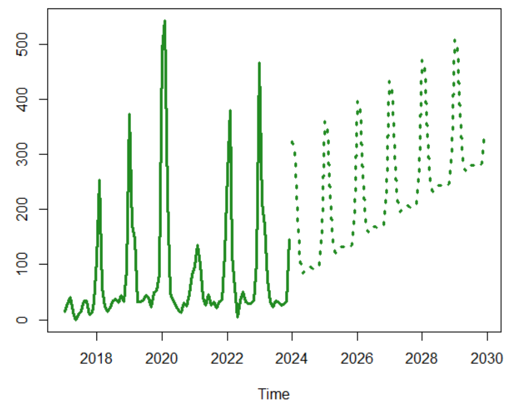

Figure 9. *Forecast of Lassa Fever Confirmed Cases for Six Years.*

3.4. Sensitivity Analysis

The two charts illustrate the sensitivity analysis of the ARIMA model (Mdl.4) which was selected as the best model based on the selection criteria, specifically its lowest AIC score., The charts compare different combinations of the P and Q parameters against performance metrics—Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results show that models with Q = 2 (blue bars) consistently achieve lower error values across all lags, indicating superior forecast accuracy. In contrast, models with Q = 0 (red bars) produce the highest error values, while models with Q =

1 (green bars) exhibit intermediate performance. This analysis suggests that increasing the seasonal moving average (MA) parameter Q enhances the model's accuracy, while the seasonal autoregressive (AR) parameter P has a more variable impact. (Figures 10 & 11). The forecasted vales for the predicted Lassa fever of the confirmed cases were also presented. The projections indicated a significant increase in Lassa fever cases over the forecasted period. (Table 3).

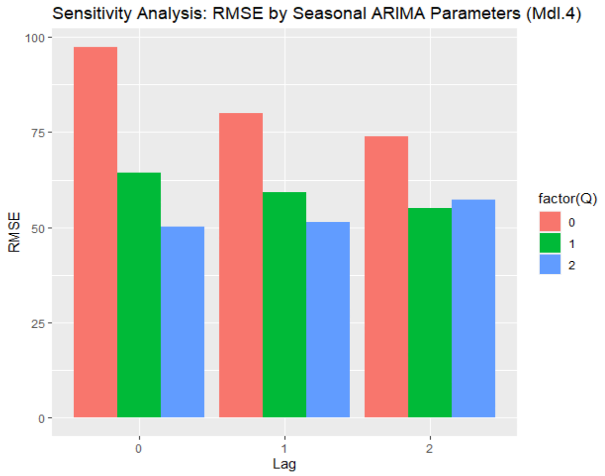

Figure 10. Sensitivity Analysis of MAE by seasonal ARIMA parameter.

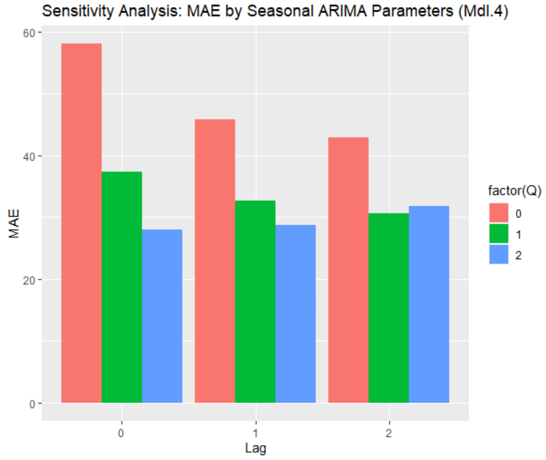

Figure 11. Sensitivity Analysis of RMSE by seasonal ARIMA parameter.

4. Discussion

Lassa fever remains a critical public health issue in Nigeria, with outbreaks spreading sporadically across the country. The study's constructed map highlights the virus's distribution, providing essential insights for effective disease control and prevention strategies. The analysis revealed varying patterns of Lassa fever distribution across various states in Nigeria. Edo State consistently emerged as one of the most heavily affected states, reporting a high number of confirmed cases throughout the study period. [10].

Table 3. Forecasted Lassa fever confirmed case 2024-2029.

Year/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2024	323	310	186	105	84	92	95	95	91	94	99	157
2025	360	347	223	142	122	129	133	132	129	131	136	194
2026	397	384	260	179	159	166	170	169	166	168	173	231
2027	434	422	297	216	196	203	207	207	203	206	210	268
2028	471	459	335	254	233	240	244	244	240	243	247	305
2029	509	496	372	291	270	277	281	281	277	280	284	342

Other states, such as Ebonyi, Bauchi, and Nassarawa, demonstrated notable levels of Lassa fever activity, highlighting the diverse spatial distribution of diverse spatial distribution of the virus. Previous research on Lassa fever indicates that the virus is endemic in states like Edo and Ondo due to the presence of the Mastomys natalensis rodent, a primary carrier of the virus, which also impacts neighboring states [11].

The virus has different pattern yearly, with 2017, the baseline year of our study witnessing a significant outbreak Cases declined from 2018 to2021 but surged again in 2023, highlighting the temporal impact on reported cases. Temporal analysis of Lassa fever outbreaks revealed varying trends in disease incidence. While some states reported sporadic cases throughout the study period, others experienced significant peaks in certain years. For example, Ondo State recorded a substantial increase in confirmed cases in 2019 and 2020, indicating localized outbreaks during those years. Bauchi State also showed a similar pattern, with a prominent increase in cases in 2019. These temporal variations underscore the dynamic nature of Lassa fever transmission, emphasizing the need for continuous surveillance and response efforts. The observed spatial and temporal patterns underline the importance of targeted interventions in high-risk areas [3].

Going through the pattern of the confirmed cases report, there is clear difference between the report during the dry and raining season. Typically, from November to March in Nigeria, there is a noticeable increase in Lassa fever cases [12]. This can be attributed to several factors such as Increased Human-rodent Interaction, this is due to the fact that dry season forces rodents to seek food in human dwellings, leading to increased contact with humans and higher transmission rats. Another factor are agricultural Activities such that the dry season coincides with the planting and harvesting seasons, increasing human activities in rural areas where rodents are abundant thereby increasing the risk of exposure to the virus. Environmental Conditions also plays a vital role in the increase of the virus, during the dry season, dusty and dry environments facilitate the survival and spread of the virus in the environment. Conversely, the raining season comes in from April to October, experiences a decline in Lassa fever cases [13]. This can be attributed to reduced Rodent activity, the raining season provides abundant food and water sources for rodents in their natural habitats, reducing the need for them to enter human dwellings. Also, during the raining season there is decreased in human outdoor activities, reducing the opportunities for humans to come into contact with infected rodents or their excreta. The pattern of the chat in Figure 3 indicates that the mean and variance of the series are stable over time. The series exhibits stationarity. Since the ADF test of stationarity shows that the series is stationary at first difference ($p<0.05$). However, since the ACF displays a sharp cut-off while the PACF decays more slowly, we say that the series displays a Moving Average signature [14]. The lags at which the ACF cuts off is the indicated number of MA order while the lags at which the PACF cuts off is the indicated number of AR order. It was obtained that the pattern is typical of ARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model.

The ARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model was selected based on the Ljung-Box Test, which indicated that the residuals of the model are uncorrelated, suggesting a good fit. With this model, we forecasted the Lassa fever confirmed cases for the next six years, from January 2024 to December 2029. The forecasted values indicate an upward trend in the Lassa fever confirmed case rate over the forecast period. The trend is depicted in Figure 6, where the dotted lines represent the six-year forecast values. While the ARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model provides a reasonable forecast based on historical data it is important to acknowledge the inherent uncertainty and potential external influences on these predictions. Sensitivity analysis of the ARIMA model shows that increasing the seasonal moving average (MA) parameter Q improves model performance, whereas the seasonal autoregressive (AR) parameter P has a more variable impact.

5. Conclusion

The study investigated the seasonal variation and predictive model approach to Lassa fever outbreaks in Nigeria from 2017 to 2023. The analysis of data from the Nigerian Centre for Disease Control (NCDC) revealed distinct temporal patterns in Lassa fever incidence, with peaks typically occurring between November and March, corresponding to the dry season. This seasonality can be attributed to factors such as increased human-rodent interaction, agricultural activities, and environmental conditions during the dry season.

The Time Series Analysis using the Box-Jenkins approach employed in this study to model the data, identify an ARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model as the most suitable for forecasting Lassa fever outbreaks in Nigeria. The forecasted model indicated an upward trend in the confirmed cases over the next six years, highlighting the importance of continuous surveillance and response efforts.

The spatial analysis showed varying patterns of Lassa fever distribution across various states in Nigeria, with Edo, Ebonyi, Ondo, Bauchi, and Nassarawa states experiencing higher burdens of the disease. These findings underscore the need for targeted interventions in high-risk areas and the importance of understanding spatial dynamics in disease transmission.

6. Recommendation

The findings of this study reveal that there is need of several recommendations to enhance the control and prevention of Lassa fever in Nigeria. Strengthen Surveillance Systems to enable early detection and response to Lassa fever outbreaks, especially during peak seasons. This could involve enhancing the capacity of healthcare workers to recognize and report suspected cases promptly. The government and other NGO's need to conduct Public Health Education campaigns to raise awareness about Lassa fever transmission, prevention, and control measures, especially in high-risk communities. Emphasis should be placed on promoting good hygiene practices and rodent control measures. Also, frequent enhanced environmental sanitation should be Implemented to reduce rodent populations in and around human settlements, such as proper waste management and environmental sanitation practices. There is need to Provide training and resources to healthcare workers, laboratory personnel, and public health officials to enhance their capacity to respond effectively to Lassa fever outbreaks. Government should support further study into the development of vaccines, therapeutics, and diagnostics for Lassa fever, as well as studies on the ecological and environmental factors influencing the transmission of the virus. There is also need to strengthen collaboration between the government, health agencies, study institutions, and international partners to improve coordination and response efforts for Lassa fever control and prevention. By implementing these recommendations, Nigeria can enhance its capacity to detect, prevent, and control Lassa fever outbreaks, ultimately reducing the burden of the disease on its population.

Abbreviations

NCDC	Nigeria Centre for disease control
ARIMA	Auto Regressive Moving Average
RNA	Ribonucleic Acid
ADF	Augmented Dickey-Fuller
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
AIC	Akaike Information Criterion
SARIMA	Seasonal Auto Regressive Moving Average
MAE	Mean Absolute Error
COVID-19	Corona Virus Disease 2019
RSME	Root Mean Square Error

Acknowledgments

We like to acknowledge Nigeria Centre for disease control (NCDC) for making the datasets open source.

Author Contributions

Adesola Musa: Conceptualization, Data curation, Formal Analysis, Methodology, Supervision, Writing – original draft

Kazeem Osuolale: Formal Analysis, Writing – review & editing

Dayo Lawal: Data curation, Formal Analysis, Methodology, Visualization

Abideen Salako: Investigation, Writing – review & editing

Fewajesuyan Aponinuola: Data curation, Methodology, Writing – original draft

Wakilat Tijani: Writing – review & editing

Abass Adigun: Writing – review & editing

Babatunde Salako: Supervision, Writing – review & editing

Funding

This work is not supported by any external funding.

Data Availability Statement

The data that support the findings of this study can be found at: https//ncdc.gov.ng/diseases/sitreps/?cat=5&name=An%20update%20of%20Lassa%20fever%20outbreak%20in%20Nigeria (a publicly available repository url)

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Emonet SF, de la Torre JC, Domingo E, Sevilla N. Arenavirus genetic diversity and its biological implications. Infect Genet Evol. 2009; 9(4): 417-29. https://doi.org/10.1016/j.meegid.2009.03.005

[2] Papageorgiou N, Spiliopoulou M, Nguyen TV, et al. Brothers in Arms: Structure, Assembly and Function of Arenaviridae Nucleoprotein. Viruses. 2020; 12(7): 772. https://doi.org/10.3390/v12070772

[3] Gibb R, Moses LM, Redding DW, Jones KE. Understanding the cryptic nature of Lassa fever in West Africa. Pathog Glob Health. 2017; 111(6): 276-88. https://doi.org/10.1080/20477724.2017.1369643

[4] Richmond JK, Baglole DJ. Lassa fever: epidemiology, clinical features, and social consequences. BMJ. 2003; 327(7426): 1271-5. https://doi.org/10.1136/bmj.327.7426.1271

[5] Panning M, Emmerich P, Olschläger S, et al. Laboratory diagnosis of Lassa fever, Liberia. Emerg Infect Dis. 2010; 16(6): 1041-3. https://doi.org/10.3201/eid1606.100040

[6] Bond N, Schieffelin JS, Moses LM, Bennett AJ, Bausch DG. A historical look at the first reported cases of Lassa fever: IgG antibodies 40 years after acute infection. Am J Trop Med Hyg. 2013; 88(2): 241-4. https://doi.org/10.4269/ajtmh.2012.12-0466

[7] Ijarotimi IT, Ilesanmi OS, Aderinwale A, et al. Knowledge of Lassa fever and use of infection prevention and control facilities among health care workers during Lassa fever outbreak in Ondo State, Nigeria. Pan Afr Med J. 2018; 30: 56. https://doi.org/10.11604/pamj.2018.30.56.13125

[8] Lupi O, Tyring SK. Tropical dermatology: viral tropical diseases. J Am Acad Dermatol. 2003; 49(6): 979-1000. https://doi.org/10.1016/s0190-9622(03)02727-0

[9] Barua S, Dénes A, Ibrahim MA. A seasonal model to assess intervention strategies for preventing periodic recurrence of Lassa fever. Heliyon. 2021; 7(8): e07760. https://doi.org/10.1016/j.heliyon.2021.e07760

[10] Ilori EA, Furuse Y, Ipadeola OB, et al. Epidemiologic and Clinical Features of Lassa Fever Outbreak in Nigeria, January 1-May 6, 2018. Emerg Infect Dis. 2019; 25(6): 1066-74. https://doi.org/10.3201/eid2506.181035

[11] Cadmus S, Taiwo OJ, Akinseye V, et al. Ecological correlates and predictors of Lassa fever incidence in Ondo State, Nigeria 2017-2021: an emerging urban trend. Sci Rep. 2023; 13(1): 20855. https://doi.org/10.1038/s41598-023-47820-3

[12] Andersen KG, Shapiro BJ, Matranga CB, et al. Clinical manifestations and response to Ribavirin among patients with Lassa fever during a hospital outbreak in Nigeria in 2012. Clin Infect Dis. 2015; 61(5): e1-9.

[13] Zhao S, Musa SS, Fu H, He D, Qin J. Large-scale Lassa fever outbreaks in Nigeria: quantifying the association between disease reproduction number and local rainfall. Epidemiol Infect. 2020; 148: e4. https://doi.org/10.1017/S0950268819002267

[14] Nasiru MO, Olanrewaju SO. Forecasting airline fatalities in the world using a univariate time series model. Int J Stat Appl. 2015; 5(5): 223-30. https://doi.org/10.5923/j.statistics.20150505.06

Biography

Adesola Musa, *Ph.D*, is a Chief Research fellow/Biostatistician at the Nigerian Institute of Medical Research (NIMR), Yaba. In the last 20 years she has worked both as a Biostatistician and a Data Manager. As a Biostatistician at NIMR, she develops and apply statistical models and theories responsible for interpreting the scientific data generated in health sciences. She is also an Adjunct Associate Professor at the Lead City University Ibadan and authored more than 120 scientific papers. Her research interest Infectious diseases, large surveys, Treatment outcome, Survival Analysis, Modelling, Implementation Science

Kazeem Osuolale is a senior research fellow/Statistician at the Nigerian Institute of Medical Research (NIMR), Yaba. His research interest is in Design and analysis of experiments, patients' monitoring, HIV/TB, Cancer Research and implementation research.

Dayo Lawal is a Reseaerch Assistant/statistician. His research interests: survey Design and analysis of experiments, Epidemiology of infectious diseases, Time series and stochastic processes, Cancer Research, Multivariate Analysis.

Abideen Salako is a Senior research fellow/pediatrician at the Nigerian Institute of Medical Research (NIMR), Yaba. His research interests are: Child and Adolescent Health, Public Health, Infectious Diseases, Sickle Cell Disease, Implementation Science Research.

Fewajesuyan Aponinuola is a medical doctor at Internal Medicine Department, Federal Medical Center Owo, Ondo State. Her research interest focused in Hematology and medical oncology, Social-ecological systems, Radiation influence, Tumor biology, Immunology, Genome biology, and Molecular biology.

Wakilat Tijani is a Research fellow/Biostatistician at the Nigerian Institute of Medical Research (NIMR), Yaba. Her research interest includes: Epidemiology of infectious diseases, Non-communicable diseases, Neglected Tropical diseases, Maternal and child health, and implementation research.

Abass Adigun is a Biostatistician at the National Centre for Remote Sensing. His research interest focused in Statistics, Geostatistical Modelling, Epidemiology, Geographic Information Science, Geocomputation, and Remote Sensing.

Babatunde Salako is a professor of Nephrology and author. He was the Director-General of the Nigerian Institute of Medical Research, Yaba Lagos from 2016-2024. his research interest includes Nephrology, Public health, clinical trials, malaria and implementation science.

Research Fields

Adesola Musa: Infectious diseases, Large surveys, Treatment outcome, Survival Analysis, Modelling, Implementation Science

Kazeem Osuolale: Design and analysis of experiments, patients' monitoring, HIV/TB, Research and implementation research

Dayo Lawal: Survey Design and analysis of experiments, Epidemiology of infectious diseases, Time series and stochastic processes, Cancer Research, Multivariate Analysis

Abideen Salako: Child and Adolescent Health, Public Health, Infectious Diseases, Sickle Cell Disease, Implementation Science Research.

Fewajesuyan Aponinuola: Hematology and medical oncology, Social-ecological systems, Radiation influence, Tumor biology, Immunology, Genome biology, and Molecular biology

Wakilat Tijani: Epidemiology of infectious diseases, Non-communicable diseases, Neglected Tropical diseases, Maternal and child health, and implemention research

Abass Adigun: Geostatistical Modelling, Epidemiology, Geographic Information Science, Geo-computation, and Remote Sensing

Babatunde Salako: Nephrology, Public Health