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Abstract

Lassa fever, a severe haemorrhagic illness induced by the Lassa virus, characterised by high morbidity and mortality rates, is endemic to West Africa, particularly Nigeria, and is mostly transmitted by *Mastomys natalensis* rats. Ondo State, a major hotspot of the disease in Nigeria, persistently endures repeated outbreaks, hence necessitating an assessment of outbreak patterns and forecast to guide public health decision in the state. This study used the seasonal auto-regressive integrated moving average (SARIMA) model to carry out a 34-week forecast of Lassa fever cases in Ondo State using Lassa fever weekly routine data. The data were split into two parts; 70% training set, used for estimating the forecasting model's parameters and 30% testing set used to evaluate

the model’s accuracy. Six candidate models were compared and the model with the least RMSE, MAE and MSE was identified. ARIMA(3,0,2)(1,0,1)[52] model showed the best fit, achieving the lowest error metrics. Diagnostic assessments were conducted to confirm the model’s adequacy prior to executing a 34-week forecast. The SARIMA model forecasted an average of 4 Lassa cases weekly over a period of 34 weeks. The forecast reveals Lassa fever peaks occurring between the 48th and 52nd weeks. The SARIMA model captured the trend and temporal variability of Lassa fever in Ondo State. The forecast suggests that the transmission of Lassa fever in Ondo State is likely to persist at moderate levels with predictable seasonal peaks. This emphasizes the need for proactive measures ahead of peak periods. These findings provide valuable insights for Ondo State public health policymakers in strengthening early warning systems and optimizing resource allocation.

Keywords: Lassa fever, Time series, Forecasting, ARIMA, SARIMA

1 Introduction

The Lassa virus, a member of the *Arenaviridae* family of single-stranded enveloped ribonucleic acid viruses, causes the hemorrhagic disease known as Lassa fever (LF). [1]. The first case was recorded in 1969 after the death of two missionary nurses [2]. The virus was given the name "Lassa virus" as the first case was found in the town of Lassa in Borno State, Nigeria [2]. Further investigations in the 1970s identified the "multimammate rat" a rodent species with more than one mammary gland. A trait that supports high reproductive rates[3]. *Mastomys natalensis* is the natural reservoir of the Lassa fever virus and this highlights a zoonotic origin of the virus in the animal-to-human interaction. Mastomys rats are ubiquitous to West African countries. They can be found living in and around homes, colonizing areas where food is stored [4].

Humans contract Lassa infection through direct contact with rodent reservoirs, ingestion of food polluted with rodent excrement and urine, or direct exposure to the body fluids of sick individuals [5]. Lassa virus is maintained within *Mastomys natalensis* populations through when infected mothers transmit the virus to their young ones during gestation, and from contact with infected bodily fluids such as urine or saliva, especially during communal nesting and grooming behaviors [6].

Infected rodents remain asymptomatic carriers throughout life, continuously shedding the virus into the environment. Symptoms of Lassa fever often appear 1–3 weeks after infection to the virus [7]. In almost 80% of cases of Lassa fever virus infections, the symptoms are mild and often go undetected [8]. Minor symptoms comprise fever, fatigue, and cephalalgia [9]. In 20% of infected individuals, the disease may advance to more severe manifestations, including haemorrhage (bleeding from the gums, eyes, or nose), respiratory distress, recurrent vomiting, facial oedema, thoracic, dorsal, and abdominal pain, and shock. Neurological complications have also been reported, encompassing hearing loss and tremors [9]. The disease is treated with the ribavirin, an antiviral drug which has been very effective when administered [10].

Humans primarily become infected through direct or indirect contact with rodents infected with LF [6]. Individuals at the most risk of contracting LF illness are those residing in rural regions where Mastomys rats are typically present, particularly in populations characterised by inadequate sanitation or densely populated living circumstances [6]. The Mastomys rats infiltrate human dwellings during the dry season in need of sustenance. The origin of LF infection in humans involves contact with the urine, faeces, blood, or flesh of LF-infected Mastomys rats[11]. Direct contact with these materials, including contact with contaminated objects, ingesting contaminated food, or exposure to open wounds, can result in infection [6].

Secondary person-to-person transmission has been documented among individuals living in overcrowded communities, family members providing care to infected persons, and during traditional burial

practices[12]. Health care workers are at increased risk of Lassa fever infection. Nosocomial transmission arises within facilities among patients as well as healthcare professionals due to inadequate compliance with infection prevention and control protocols. Transmission can also occur through exposure to bodily secretions, accidental needle-stick injuries, or contact with contaminated equipment [13]. LF outbreaks in extensive healthcare institutions are exacerbated by transmission due to insufficient barrier nursing and infection control measures. Personnel and other patients in maternity wards face heightened risk due to Lassa fever, which significantly contributes to spontaneous abortion, with the virus detectable in the blood and placenta of aborted fetuses [14].

There have been reports of sexual transmission occurring months after recovery from acute disease [15]. Disease outbreaks seem to occur commonly through multiple independent reservoir-to-human transmissions. The period of infectivity in patients with Lassa fever depends on their clinical condition, with the peak infectivity happening later in the course of severe disease, particularly during the hemorrhagic phase [6]. Personnel and other patients in maternity wards face heightened risk due to Lassa fever, which significantly contributes to spontaneous abortion, with the virus detectable in the blood and placenta of aborted fetuses [16]

Lassa fever can affect individuals of all ages and both sexes [17]. In children who exhibit generalised oedema, abdominal distension, and haemorrhage, the case fatality rate may approach 30% when the illness presents as an acute febrile illness [18]. Factors influencing the escalation of LF transmission and its spillover into human populations comprise seasonal variations, urbanisation, environmental sanitation, deforestation, and the incidence of disasters leading to forced migration [19].

LF is endemic in some countries of West Africa including Nigeria, Guinea, Liberia, and Sierra Leone. Other West African nations such as Togo, Benin, Mali, Côte d'Ivoire, Ghana and Burkina Faso have documented intermittent instances of Lassa fever [9]. In Nigeria, it is remaining a recurrent public health burden, particularly in Ondo State, which contributes over 30% of the confirmed cases in the country [20]. According to the Nigerian Center for Disease Control and Prevention (NCDC), as of June 2025 (up to week 23), the case fatality rate (CFR) stands at 18.9%, reflecting a slight increase compared to 17.8% recorded in 2024[21]. However, there has been a notable decrease in the number of confirmed cases during the same period, with 758 cases in 2025 compared to 911 in 2024 [22].

Lassa fever caused a cumulative 214 confirmed deaths in 2024, 227 deaths for 2023 and between Week 1 to 23, a cumulative 143 confirmed deaths have occurred, spreading across 18 states and 96 local governments, with 90% of all confirmed cases reported from Ondo, Bauchi, Edo, Taraba and Ebonyi at 31%, 25%, 16%, 15% and 3% respectively[22]. While 10% was reported for other states, the primary affected age group is 21 to 30 years, with a median age of 30 within a range of 1 to 96 years. The male-to-female ratio for confirmed cases is 1:0.8 [22].

LF poses a significant risk to healthcare in Nigeria and other vulnerable African countries [23]. Several efforts have been put in place to improve the awareness of the disease and other preventive mechanisms to reduce the disease burden, especially with the global shift from curative to preventive medicine [24]. Challenges of late detection, poor sanitation, and limited access to diagnostics have kept the Nigeria Centre for Disease Control and Prevention (NCDC) on its toes and the national incident management systems activated [22]. In high-burden zones like Ondo, epidemiological surveillance is hampered by the underreporting and misdiagnosis of Lassa fever owing to its symptom overlap with diseases like malaria. This, therefore, explains the need for an effective early warning system to mitigate the spread of Lassa fever in the society.

While medical researchers have concentrated efforts on enhancing laboratory diagnostics, accelerating Lassa virus (LASV) identification, and developing effective therapeutics and vaccines, bi-mathematicians and natural scientists have focused on mathematical modeling of the disease's transmission dynamics and control strategies across different host populations [25]. Research findings have shown that people with health related conditions like HIV, tuberculosis and cancer have high risk of getting infected with LF. [26]. The spread of infectious disease like Ebola, COVID-19, Cholera, and Measles has been mitigated by the use of forecasting models [27].

Forecasting models have become more significant in recent years, mostly for newly emerging disease

outbreaks and it plays a crucial role in addressing public health challenges and efficiently manage outbreaks [28].

[29] Examined datasets from 2017 to 2023 for seasonal fluctuations and forecasted future incidences of Lassa fever. The findings indicated clear seasonal trends in Lassa fever incidence, shaped by Nigeria's climatic and environmental factors, with peak occurrences coinciding with particular seasons. The study employed the Box-Jenkins time series analysis, specifically the ARIMA (0, 1, 1)(0, 1, 1)₁₂ model that demonstrated a strong fit to the data providing reliable forecasts for future outbreaks. The model's accuracy was evaluated using the Ljung-Box test, while geo-spatial analysis illustrated the distribution of cases across various locations. The research emphasised the necessity of enhancing surveillance systems for the prompt identification and swift response to Lassa fever outbreaks, especially during peak periods.

A weekly incidence of Lassa Fever from Edo state, Nigeria was analyzed by [30] using two methods of fitting distributions to data, the Kolmogorov-Smirnov test of goodness of fit and the Anderson-Darling test and found that the occurrence pattern most closely fit a geometric distribution. This statistical perspective of analyzing the outbreak pattern forms a logical base for model prediction. Their work concludes at distribution analysis and, thus, hints towards more sophisticated forecasting techniques, an area this study intends to fill with a model for an early warning system for Lassa Fever outbreaks.

[31] thus modeled the 2021 Lassa fever outbreak experienced in Nigeria as a syndemic along with COVID-19 and cholera outbreaks ongoing at the time. Using Poisson regression, cholera n and SARIMA forecasting models, it found out that the predictors of Lassa fever cases included the COVID-19 occurrence, seasonality, and geographic distribution. The variance in the cases accounted for by the study was 48.1%, indicating that time-series predictive modeling can be done even in a very complicated epidemic landscape. This study indicates the benefit that is brought in by multi-factorial early warning systems and methods on which the proposed predictive model for the threat of Lassa fever lies.

[32] developed a predictive model for Lassa Fever in Ondo State, Nigeria using a Bayesian linear regression method. The study employed Bayesian ridge regression to predict outbreak patterns with high accuracy indicating strong predictive performance. The results highlight the model's effectiveness for targeted intervention and outbreak control.

A review of Lassa fever epidemiology in Nigeria was carried out by [33] highlighting its rodent-to-human and secondary human transmission, with high morbidity and mortality. The disease peaks during the dry season (December–March) and severely affects public health and livelihoods. Control efforts include the Integrated Disease Surveillance and Response Strategy (IDSR) and other medical strategies in endemic regions.

Another study was carried out by [30] on the ecological correlates and predictors of Lassa fever in Ondo State from 2017 to 2021, which included an analysis of the distributional pattern of persons diagnosed with Lassa fever at different locations in the state. The study investigated the correlation and determinants of Lassa fever incidence and ecological variables occurrence using nearest-neighbor statistics, regression analysis, and GIS for spatial position with higher opportunities to scale analysis. The study showed that from 2017 to 2021, there were spatio-temporal clustering of LF cases, showing an upward trajectory followed by a downward trend in 2021.

[34] used descriptive statistics, an additive time series model, a quadratic equation, and a logistic regression model ($\alpha = 0.05$) to develop a model that would assess the epidemiology of Lassa fever, its seasonality, trends, and predictors of mortality in Ebonyi State, South-East Nigeria. ArcGIS was used to perform the spatial analysis of reported cases of Lassa fever. The trend on the cases of Lassa fever recorded in the Ebonyi state were downward with seasonal trend on the occurrence of the disease.

A time series study by [35] applied ARIMA model for a 14-month forecast of mpox cases and mortality in Nigeria. The study utilised mpox monthly routine data that was split into 70% train set and 30% test set. To further uncover hidden features, wavelet analysis was used to decompose the time series into its frequency components. The wavelet power spectrum revealed a persistent yearly cycle between mid 2022 and June 2023, which implies a seasonal cycle with a strong anomaly or peak, with a single event leading to an increase in mpox cases in Nigeria, followed by a return to baseline.

Several other research works have been carried out using ARIMA and SARIMA models to predict the outbreaks of various diseases such as tuberculosis, Cholera, Malaria, COVID-19 etc. [36, 37, 38, 39, 40, 41].

Models such as ARIMA and Poisson regressions have been approached in many studies of Lassa fever; they are inadequate for most sparse, nonlinear, and noisy surveillance data. The incorporation of ecological, demographic, and syndromic features into predictive algorithms is still underexploited. In addition, very few have operationalized these models into a full real-time early warning system.

The collective literature emphasizes the urgent need for forecasting systems that will couple machine learning, climate trends, geospatial analysis, and public health surveillance in combating Lassa fever across hotspots like Ondo State. Such models must be dynamic, tailored to local conditions, and housed under a substantial health infrastructure and mechanisms for public engagement. Hence, the need for developing early warning systems using predictive models.

2 Materials and Methods

2.1 Study Area

The research utilised data on confirmed cases of Lassa Fever from Ondo State, Nigeria. Ondo State is situated in the southwestern part of Nigeria. The State is positioned between latitudes $5^{\circ}45'$ and $8^{\circ}15'$ North and longitudes $4^{\circ}45'$ and 6° East, signifying its complete location inside the tropics. It is bordered to the northwest, west-central, southeast and south by Ekiti State, Osun State, Ogun State, Delta State, and the Atlantic Ocean respectively. It consists of 18 local government units, with Akure serving as the state capital. The National Population Commission estimates that Ondo State's population was 5,316,000 in 2022, with an annual growth rate of around 2.7% [42]. Figure 1 presents a map of Nigeria showing where Ondo state is situated

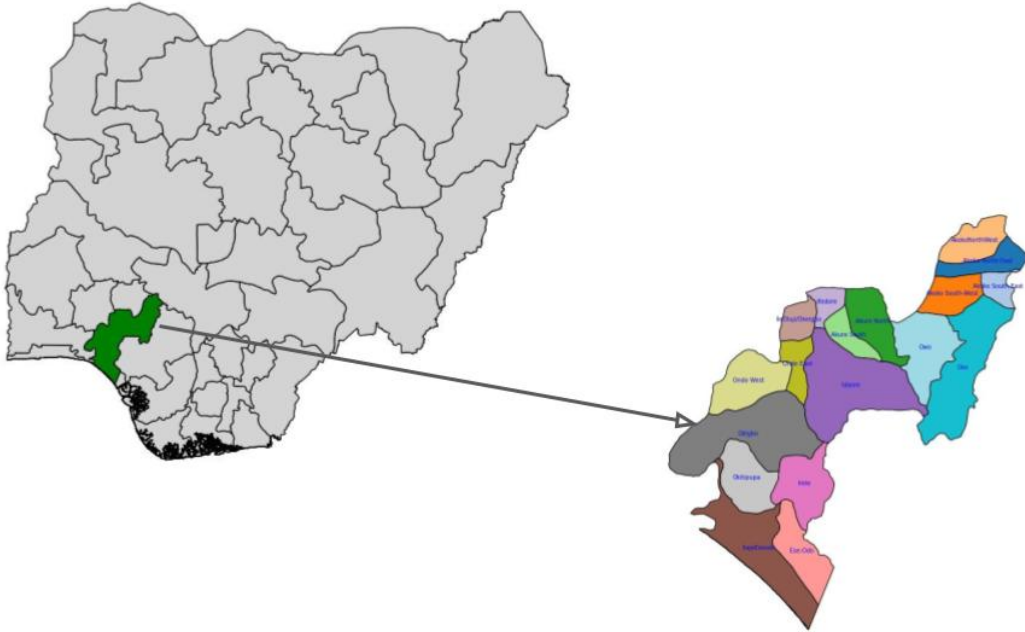


Figure 1: Geographical representation of Nigeria highlighting Ondo State (in green), with a detailed view of Ondo State's local government areas (LGAs). The arrow illustrates the spatial connection between the state's national context and its internal administrative divisions.

2.2 Data description

The data set used in this study comprises weekly confirmed cases of Lassa Fever in Ondo State, spanning a period of 382 weeks - from January 2018 to April 2025. Data for confirmed cases in Ondo state were sourced from NCDC. The dataset includes 382 observations and one variable, the number of confirmed cases, each representing a week.

2.3 Auto-Regressive Integrated Moving Average (ARIMA) Model

ARIMA model was first introduced in 1976 by two researchers named Box and Jenkin [43]. It is utilised for predicting non-seasonal stationary time-series data. An ARIMA model is defined by three parameters: p, d , and q , where p denotes the order of the Auto-Regression (AR) component, q signifies the order of the Moving Average (MA) component, and d represents the degree of differencing necessary to achieve stationarity in the time series. Auto-regression refers to the regression of a variable upon itself to predict the variable of interest. It correlates the pattern of a singular time period to its antecedent time periods. MA is a regression-type model that employs the errors from prior forecasts to predict a variable at a subsequent time-step. The following are the generalized equations of p th order AR model (Eq. (1)) and q th order MA model (Eq. (2)).

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + E_t \quad (1)$$

$$y_t = C + E_t + \theta_1 E_{t-1} + \theta_2 E_{t-2} + \cdots + \theta_q E_{t-q} \quad (2)$$

ARIMA models are built upon incorporating the AR model (Eq. (1)), integration (I) and the MA model (Eq. (2)). The integration (I) is the reverse process of differencing to generate the forecast. The generalized ARIMA model is mathematically represented as in Eq. (3).

$$y_t = C + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 E_{t-1} + \cdots + \theta_q E_{t-q} + E_t \quad (3)$$

Where C is intercept, ϕ_i ($i = 1, 2, \dots, p$) is auto-regressive model parameters, θ_i ($i = 1, 2, \dots, q$) is moving average model parameters, y_t is current time-series value, $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ are past values and E_t is random error or residual term for the t^{th} day and it is given by the following equation:

$$E_t = y_t - y_{t-1} \quad (4)$$

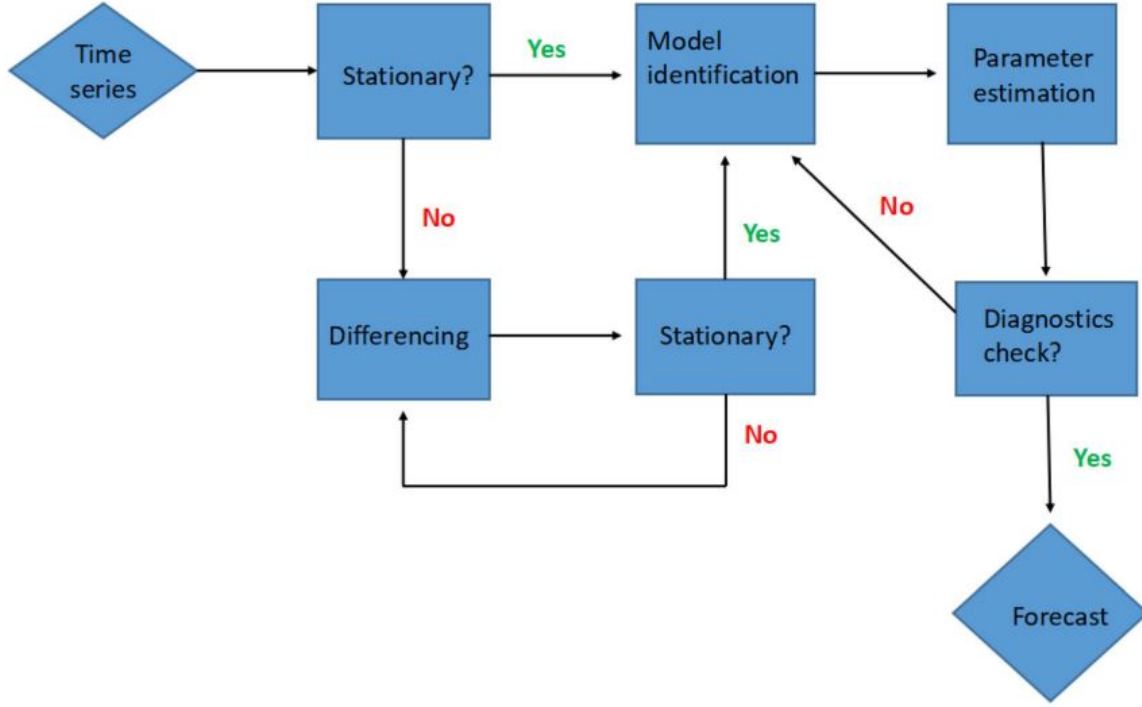


Figure 2: Flow chart of ARIMA forecasting process Source [35]

2.4 Seasonal ARIMA (SARIMA) Model

The SARIMA model is an important statistical approach commonly used for analyzing and forecasting time series data that exhibit both trend and seasonal behaviors. This model has proven effective in public health settings, especially for diseases such as Lassa fever that display regular seasonal patterns. LF usually peaks during the dry season—typically between December and April in West Africa. This seasonal surge is closely tied to ecological and behavioral changes in *Mastomys* rodents, the primary reservoirs of the virus, along with variations in human exposure and climatic conditions [44, 45, 46].

The SARIMA model is a generalization of the ARIMA model that includes seasonal elements. It is typically represented as $\text{SARIMA}(p, d, q)(P, D, Q)_s$, where p , d , and q denote the orders of the non-seasonal autoregressive, differencing, and moving average components, respectively, while P , D , and Q signify the seasonal equivalents. The subscript s represents the seasonal period. The seasonal period for weekly Lassa fever incidence data is often established at $s = 52$, indicating annual seasonality.

Mathematically, the SARIMA model is expressed as:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D L_t = \theta(B)\Theta(B^s)\varepsilon_t,$$

where L_t denotes the number of Lassa fever cases at time t , B is the backshift operator, and ε_t is assumed to be a white noise error term. The functions $\phi(B)$ and $\theta(B)$ capture the non-seasonal AR and MA parts respectively, while $\Phi(B^s)$ and $\Theta(B^s)$ represent the seasonal AR and MA terms.

The modelling process begins with a stationarity check. Since time series models assume stationarity, it is important to test whether the Lassa fever data fulfill this requirement. The Augmented Dickey-Fuller (ADF) test is a widely used method for this purpose [47]. If the data are non-stationary, differencing—both seasonal and non-seasonal—is applied accordingly.

Once stationarity is achieved, the next step is model identification. This entails evaluating the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to ascertain suitable values for the parameters p , q , P , and Q . After the proposal of the basic model structure, parameter estimation is conducted utilising Maximum Likelihood Estimation (MLE). The `auto.arima()` function in R automates the selection of the model with the lowest information criterion. [48].

Following estimation, model diagnostics are essential to ensure the validity of the fitted model. This typically involves analyzing residuals and applying the Ljung-Box test to verify for autocorrelation in

the residual series [49]. Adequate models should have residuals that approximate white noise. Once diagnostic checks confirm model adequacy, forecasting can be conducted. SARIMA-based forecasts help detect early warning signals by projecting disease incidence into the future [50].

The SARIMA model is particularly suited for Lassa fever forecasting because it captures the seasonal peaks associated with rodent-to-human transmission dynamics [51]. In addition to modeling seasonal variability, it accurately considers both short term variations and long term disease patterns. The model offers a statistically robust framework that facilitates decision-making in public health by identifying early warning signs and anticipating probable outbreaks [52].

2.5 Model Evaluation Metrics

In developing early warning systems for Lassa fever threats in Ondo State, Nigeria, it is not enough to build a predictive model such as SARIMA; the accuracy and reliability of the model must also be evaluated. Model evaluation metrics provide a way to assess how well the model fits the data and how accurately it forecasts future cases. In this study, four commonly used evaluation metrics are employed: Akaike Information Criterion (AIC), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE). These metrics give key insights into the performance of the predictive model [53].

Akaike Information Criterion (AIC)

The AIC [54], is a statistical measure used to compare various models and choose the one that best balances goodness of fit and model simplicity. It penalizes models with too many parameters to prevent overfitting. It is given as:

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

where k is the number of model parameters that are estimated and L denotes the maximum value of the model's likelihood function.

In the context of this study, AIC is used to select the most appropriate SARIMA model for forecasting Lassa fever cases. The model with the lowest AIC value is considered the best, as it explains the patterns in the data without being overly complex [55].

2.6 Root Mean Squared Error (RMSE)

The RMSE quantifies the average magnitude of prediction errors by calculating the square root of the mean of the squared discrepancies between observed and forecasted values [56]. The formula is:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where y_i is the observed values, $\hat{y}_i$ is the predicted values, and n is the number of observations.

RMSE is particularly useful because it gives errors in the same units as the data. For Lassa fever forecasting, a lower RMSE means the SARIMA model predictions are closer to the actual reported cases, indicating higher accuracy.

2.7 Mean Absolute Error (MAE)

The MAE quantifies the average magnitude of discrepancies between observed and expected values by utilising the absolute values of the differences, hence preventing the cancellation of positive and negative errors [57]. The formula is:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

In this study, MAE represents the average difference between the predicted Lassa fever incidence and the actual reported cases. It is easy to interpret: for example, an MAE of 5 means the model's predictions are off by about 5 cases on average.

2.8 Mean Squared Error (MSE)

The Mean Squared Error (MSE) measures the average of the squared differences between observed and predicted values. Unlike MAE, it penalizes larger errors more heavily, making it sensitive to outliers [58]. The formula is:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

In forecasting Lassa fever cases, a lower MSE indicates that the SARIMA model is capturing the disease dynamics more accurately. A higher MSE suggests that the predictions deviate significantly from the actual cases.

Data Analysis and Presentation of Results

Exploratory Data Analysis

The study began with an exploratory analysis of weekly reported cases of LF in Ondo State from 2018 to 2023.

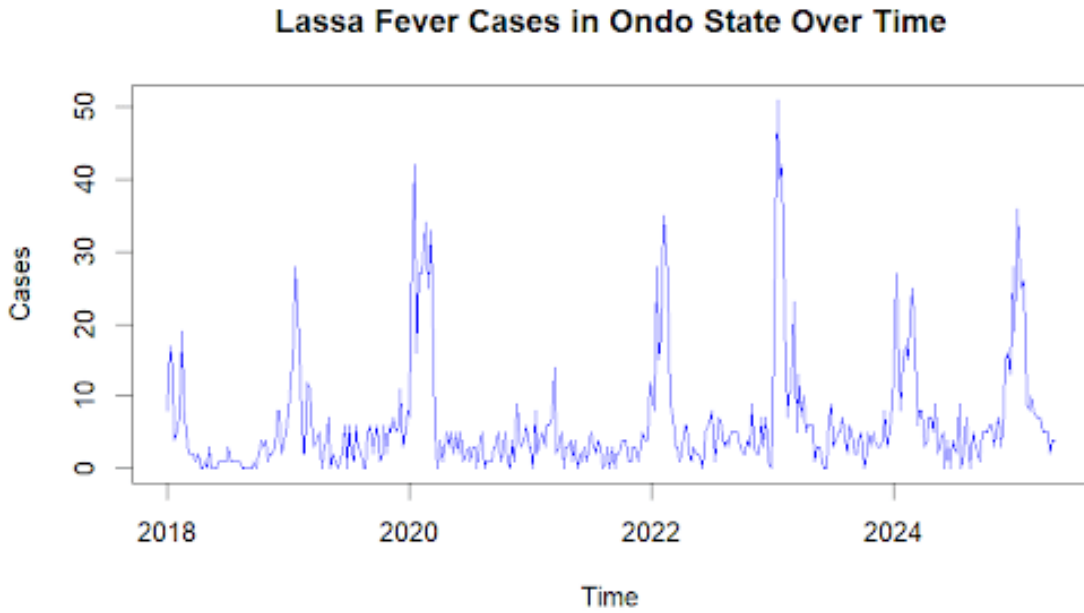


Figure 3: Time Series plot of LF cases in Ondo State from Jan 2018 - May 2025

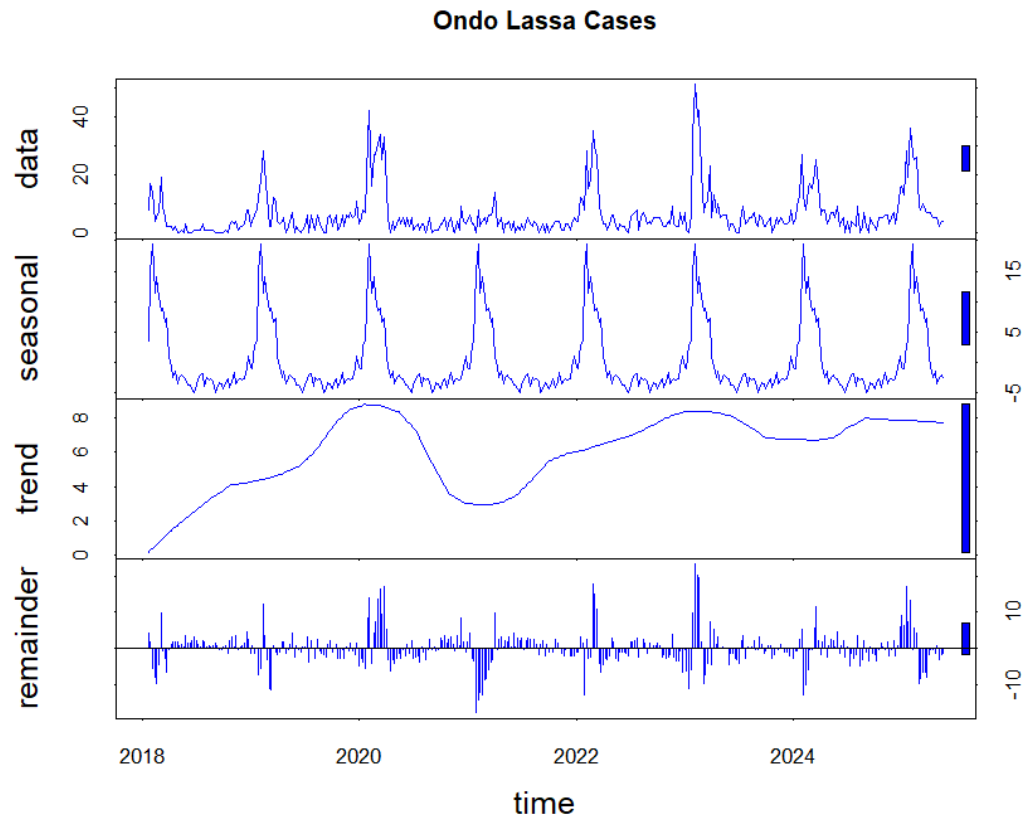


Figure 4: STL Decomposition of Time series plot of LF cases in Ondo State from Jan 2018 - May 2025

2.9 Stationarity Check

2.10 Data Partitioning

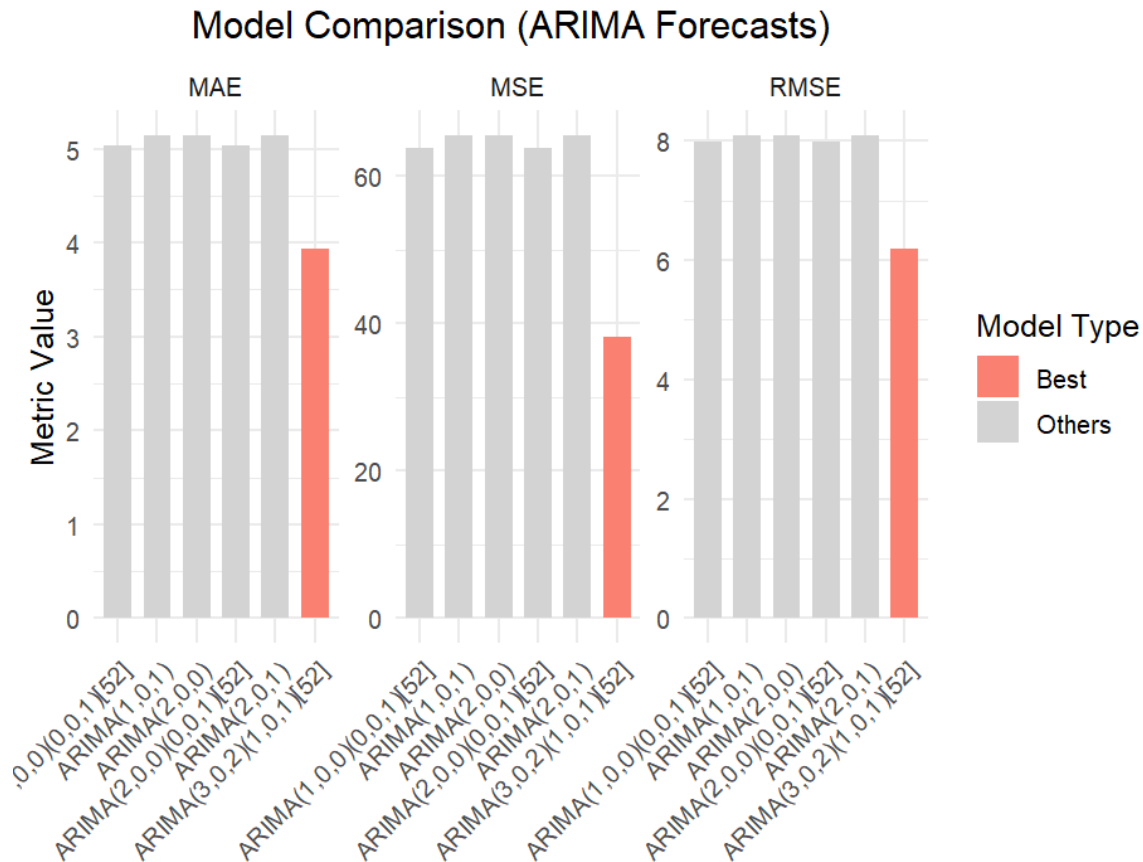


Figure 5: Model Comparison using RMSE, MAE, and MSE.

2.11 Forecasting Results

Table 1: ARIMA Forecasts with Prediction Intervals from the 19th week of 2025 - the 52nd week of 2025

Weeks	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
19	3.145	-2.960	9.249	-6.191	12.481
20	3.291	-4.074	10.656	-7.972	14.555
21	4.379	-3.633	12.391	-7.874	16.632
22	4.105	-4.264	12.473	-8.694	16.903
23	2.883	-5.619	11.386	-10.121	15.887
24	2.881	-5.648	11.409	-10.163	15.924
25	3.849	-4.685	12.384	-9.203	16.901
26	5.261	-3.285	13.807	-7.809	18.331
27	5.688	-2.879	14.255	-7.415	18.790
28	3.910	-4.667	12.487	-9.207	17.027
29	4.053	-4.524	12.629	-9.064	17.170
30	3.773	-4.806	12.352	-9.347	16.894

Continued on next page

Weeks	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
31	4.700	-3.879	13.279	-8.421	17.820
32	4.953	-3.630	13.535	-8.173	18.079
33	3.463	-5.124	12.050	-9.669	16.595
34	3.113	-5.474	11.699	-10.019	16.245
35	3.627	-4.963	12.216	-9.510	16.764
36	4.035	-4.555	12.626	-9.103	17.174
37	4.059	-4.532	12.651	-9.081	17.199
38	4.514	-4.081	13.108	-8.631	17.658
39	4.483	-4.112	13.077	-8.662	17.627
40	3.159	-5.437	11.755	-9.988	16.306
41	4.081	-4.517	12.679	-9.069	17.231
42	5.595	-3.004	14.193	-7.555	18.744
43	4.526	-4.074	13.126	-8.627	17.679
44	4.546	-4.055	13.146	-8.608	17.699
45	4.245	-4.356	12.846	-8.909	17.399
46	4.285	-4.317	12.888	-8.871	17.442
47	4.806	-3.797	13.409	-8.351	17.963
48	6.261	-2.343	14.864	-6.897	19.419
49	7.148	-1.455	15.752	-6.009	20.306
50	5.526	-3.075	14.127	-7.628	18.680
51	5.415	-3.184	14.013	-7.736	18.565
52	8.306	-0.288	16.900	-4.837	21.449

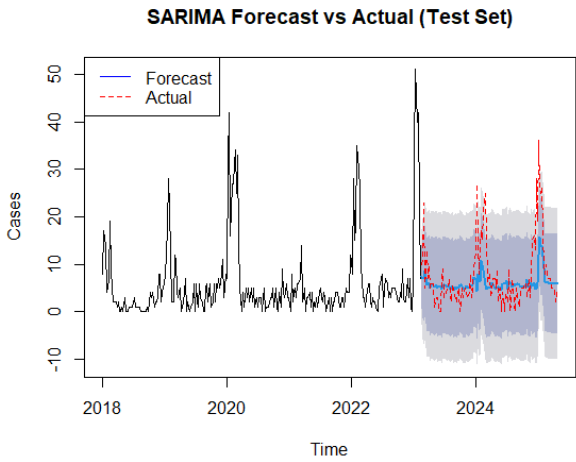


Figure 6: SARIMA Forecast vs Actual (Test Set)

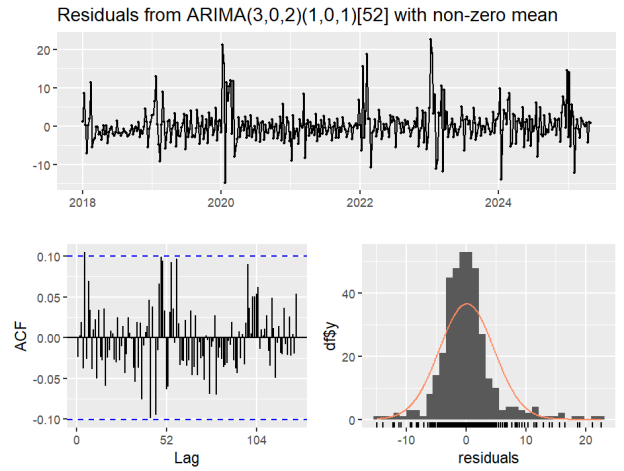


Figure 7: Residuals from ARIMA(3,0,2)(1,0,1)[52]

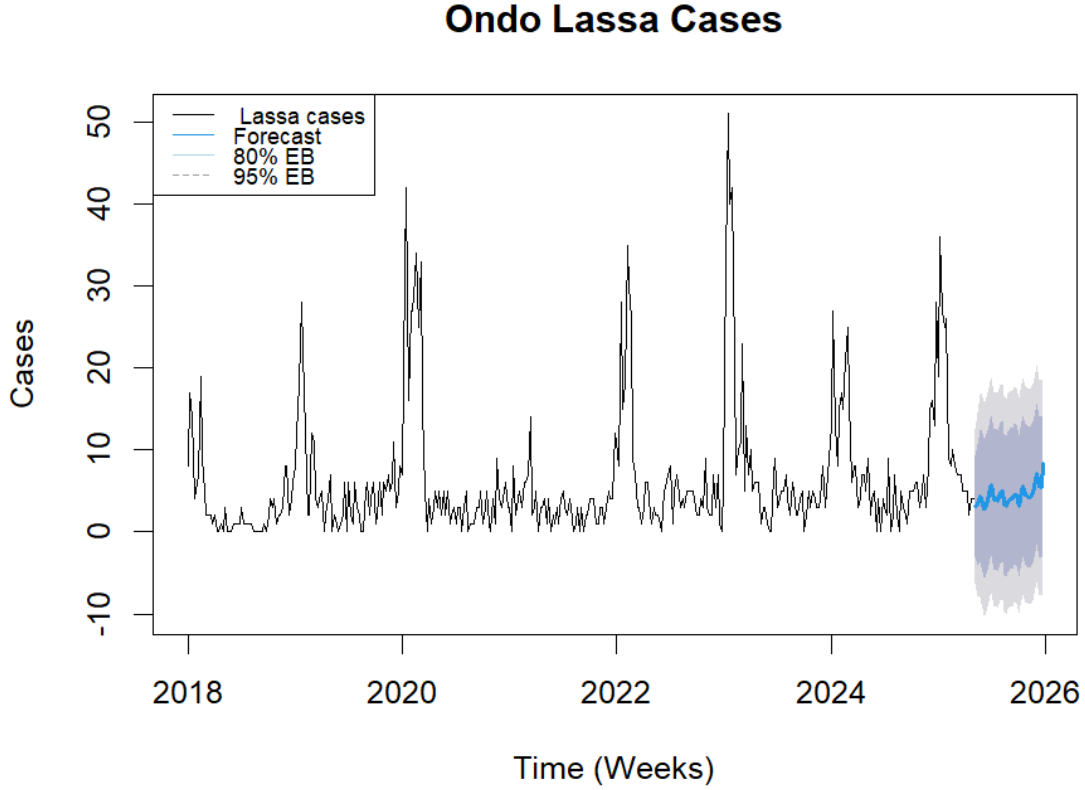


Figure 8: **SARIMA** Forecast of Lassa Fever cases in Ondo State from the 18th week of 2025-52nd week of 2025

3 Results and Discussions

The time series plot of reported LF cases in Ondo State is shown in Fig. 3. The plot depicts weekly data spanning from January 2018 to December 2025. The y-axis (labeled “Number of cases”) shows the raw weekly counts, while the x-axis represents time in weeks. The plot reveals a distinct seasonal pattern with strong spikes nearly every year between January and March, coinciding with the dry season when transmission risk is highest. The outbreaks vary in severity, with particularly high peaks in early 2020 and 2023, followed by sharp declines that sometimes fall close to zero. These recurring spikes emphasize the endemicity of Lassa fever in Ondo State and highlight the need for increased preparedness at the beginning of each year.

Fig. 4 illustrates the decomposition of the time series. The STL decomposition divides the data into trend, seasonal, and residual components. The trend indicates alternating periods of rising and falling case loads, while the seasonal component confirms annual peaks occurring consistently between January and March. The remainder captures irregular fluctuations, suggesting that epidemic severity is influenced by both systematic seasonal drivers and random shocks.

The dataset was split into two: training (70%) and testing (30%). `Auto.arima()` function in R was applied on the training set to generate candidate models. Six ARIMA models with varying AR, MA, and seasonal components were evaluated, with their performance compared using Akaike Information Criterion (AIC) values. Among these, the $ARIMA(3,0,2)(1,0,1)_{[52]}$ model achieved the lowest AIC and was selected as the best-fitting model.

The predictive quality of the candidate models was further assessed using three evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), as presented in Fig. 5. The $ARIMA(3,0,2)(1,0,1)_{[52]}$ model consistently achieved the lowest error values, confirming its superior forecasting accuracy.

Diagnostic tests were also conducted on the residuals of the selected $\text{ARIMA}(3,0,2)(1,0,1)[52]$ model to verify its adequacy. As shown in Fig. 7, the residuals were approximately normally distributed and randomly scattered around zero with no significant autocorrelation. The Ljung–Box test yielded p-values much greater than 0.05, showing that the temporal structure of the data was effectively captured by the model.

The model performance was evaluated by comparing the fitted values from the training set with the actual values in the test set. Fig. 6 presents the train–test plot, where the fitted series (blue line) is compared against the observed case counts (red dashed line). The plot shows that the model was able to capture the major seasonal spikes and general epidemic patterns of Lassa fever. The prediction intervals (shaded regions) covered most of the observed values in the test data, suggesting that the $\text{ARIMA}(3,0,2)(1,0,1)[52]$ model provides a reliable representation of the underlying dynamics of the disease.

The forecast horizon for 2025 is shown in Fig. 8. The $\text{ARIMA}(3,0,2)(1,0,1)[52]$ model predicts moderate case levels, mostly between 5 and 15 per week from the 19th to 52nd week of the year. The majority of forecasted values lie within the 80% and 95% prediction intervals. Unlike the historical data, which features sudden outbreak peaks, the model projects a relatively stable trend without catastrophic surges. These findings confirm that Lassa fever remains endemic in Ondo State with predictable seasonal epidemics, but forecasts suggest moderate transmission levels under stable conditions.

4 Conclusion

A SARIMA model was developed to forecast Lassa fever incidence over 34 weeks in Ondo state, Nigeria, using routinely collected weekly surveillance data. The model efficiently captured both the short-term and the long-term seasonal variations associated with Lassa fever transmission. The results indicated a distinct seasonal pattern with pronounced peaks typically observed between January and March nearly each year, coinciding with the dry season when human exposure to infected rodents is elevated. Among the tested models, SARIMA (3, 0, 2) (1, 0, 1) configuration achieved the lowest AIC value and the smallest prediction errors across the evaluation metrics, RMSE, MAE, and MSE, thus identifying it as the most suitable model. Diagnostic evaluations confirmed that the residuals were normally distributed and randomly scattered with no significant autocorrelation, thereby validating the robustness and adequacy of the model. Comparison between the observed and the fitted values demonstrated that the $\text{ARIMA}(3, 0, 2)(1, 0, 1)[52]$ model accurately reproduced the major seasonal spikes and the overall epidemic trend of the Lassa fever in the study area. These findings indicate that Lassa fever remains endemic in Ondo state, exhibiting predictable seasonal epidemics. The forecast further suggests a moderate transmission level under stable environmental conditions.

Declarations

Ethics approval and consent to participate

This study involved the secondary analysis of fully anonymized, aggregate data obtained from the National Centre for Disease Control and Prevention. Ethical review and approval were waived for this study as it did not involve direct interaction with human subjects or access to identifiable personal information.

Consent for publication

Not applicable

Availability of data and materials

The weekly reported lassa fever cases data were obtained from <https://ncdc.gov.ng/data>.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

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SDO: Project administration, writing - review and editing, supervision

DAB:Methodology, project administration, writing - original draft, writing - review and editing, software

DDD: Methodology, writing - original draft, software

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