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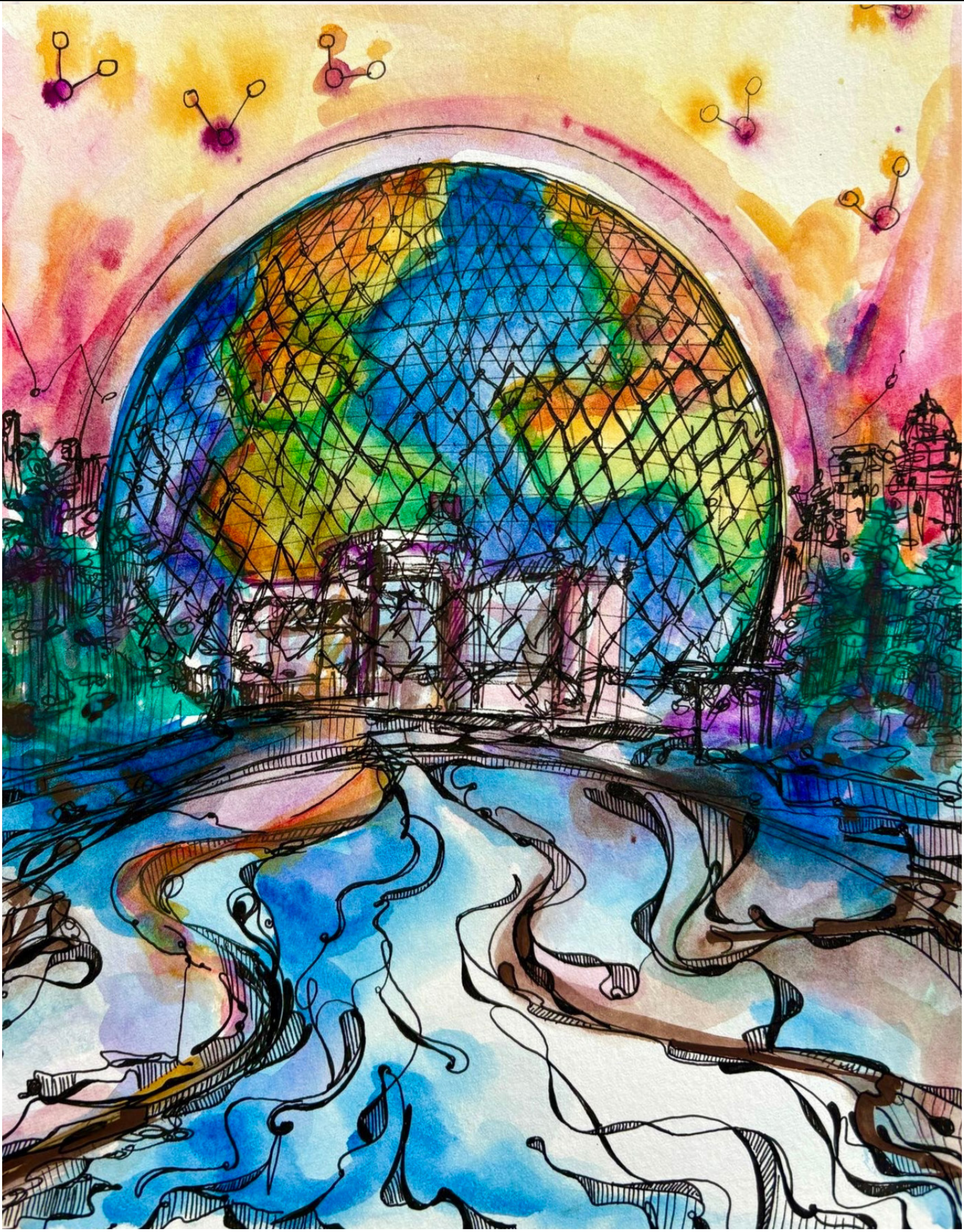

Time Series Analysis of Measles Incidence in Nigeria Using Surveillance Data from 2011 to 2022

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Abstract

Background: Measles is a highly contagious viral disease that primarily affects children, especially in underdeveloped nations. In Nigeria, inadequate vaccine coverage has sustained measles endemicity. This study analyzed the trend and seasonality of measles in Nigeria and forecasted its trajectory from January 2023 to December 2026. **Methods and Materials:** Time series analysis was applied to laboratory-confirmed measles cases from the World Health Organization case-based surveillance data reported in Nigeria from January 2011 to December 2022. The analysis was conducted using Seasonal and Trend decomposition using Loess and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, with model selection determined by the Akaike Information Criterion and validated using residual diagnostics. Measles incidence forecasts for 2023 to 2026 were generated, with predictive accuracy assessed using the root mean square error and mean absolute error (MAE). **Results:** A total of 203,587 measles cases were reported during this period, with an average incidence of 7.5 cases per one million individuals. Seasonal peaks were consistently observed from January to March, with no discernible long-term trend. The SARIMA (3, 0, 1)(1, 1, 1)$_{12}$ model demonstrated the best fit for forecasting, achieving an MAE of 3.2 cases per one million population when comparing predicted and observed incidence in 2023. Forecasts suggest the seasonal patterns and magnitudes will persist through 2026, assuming all factors remain constant. **Conclusion:** This study highlights seasonal peaks in measles incidence from January to March in Nigeria, highlighting the urgent need for improved vaccination coverage and targeted public health interventions during peak seasons to mitigate the disease burden.

Keywords: Measles incidence; Seasonality; Time series analysis; Prediction; Nigeria

Introduction

Measles, historically a leading cause of child mortality, is a highly contagious vaccine-preventable disease caused by Morbillivirus [1]. Transmission primarily occurs through aerosol droplets or oral secretions from infected to susceptible individuals, particularly children under 17 years of age [2]. Symptoms typically appear 10 to 15 days after exposure and include fever, cough, rash, and generalized body aches [3].

Measles exhibits a seasonal pattern, peaking during colder and drier seasons, particularly in tropical climates of endemic countries [2]. The World Health Organization (WHO) recommends administering the first dose of a measles-containing vaccine (MCV1) to infants at nine months in endemic regions and between 12 to 15 months in non-endemic countries [4]. To ensure adequate immunity, a second dose (MCV2) is included in routine immunization schedules to protect individuals who may not develop sufficient immunity after the MCV1. This two-dose strategy significantly enhances population immunity and is essential in regions with high measles transmission rates [2].

The global incidence of measles decreased by approximately 88% from 2000 to 2016 [5]; however, progress in controlling the disease has been significantly hindered by inadequate vaccination coverage in many developing countries. This shortfall has resulted in the resurgence and re-establishment of endemic measles transmission [6-7]. To achieve measles elimination, the WHO aims to reach at least 95% immunization coverage with the MCV1 at both national and district levels, while also reducing the incidence to fewer than 5 cases per million individuals. These targets are essential for sustained progress in measles eradication efforts [8].

According to the U.S. Centers for Disease Control and Prevention, over sixty million measles vaccine doses were delayed or not administered globally due to the COVID-19 pandemic [9]. In a developing country like Nigeria, the situation is particularly severe, with the country ranking fourth among those facing major global measles outbreaks. Contributing factors include a substantial number of unvaccinated children, low routine immunization coverage, and heightened susceptibility among the population [9-10]. In 2015, approximately three million of the global total of 20.8 million infants lacking the MCV1 were in Nigeria [2]. Given the ongoing measles burden in Nigeria and the risk of future outbreaks, understanding incidence patterns over time is essential for improving disease surveillance and response. Thus, this study investigates the trend and seasonality of measles in Nigeria through case-based surveillance data spanning January 2011 to December 2022, with a subsequent four-year forecast starting from January 2023. The research aims to provide a valuable reference for strategies in mitigating and eliminating measles in Nigeria.

Methods and Materials

The study utilized data obtained from the official website of WHO, which included laboratory-confirmed measles cases reported monthly in Nigeria from January 2011 to December 2022 [11]. Population estimates for Nigeria during this period were retrieved [12]. The incidence risk of measles was calculated for each month by dividing the monthly cases by the estimated annual population and multiplying the result by one million. This method allowed for a standardized incidence risk per million population [13]. Statistical analyses were conducted using Stata and R for descriptive statistics and time series analysis, respectively [14-15]. The time series analysis utilized Seasonal and Trend decomposition using Loess (STL) based on Cleveland's approach (a method that effectively separates trend, seasonality, and residual components in nonstationary time series data, making it well-suited for analyzing measles incidence patterns), and the Durbin-Watson test for autocorrelation assessment using a two-sided alternative hypothesis [16, 17]. These methods allowed for a comprehensive understanding of the trends and seasonal patterns in the data.

Following Box and Jenkins' iterative modeling steps, the study assessed the need for differencing during STL and applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to the data to filter out seasonal effects and achieve stationarity [18]. The SARIMA model's parameters (p, d, q) (P, D, Q) s were estimated, with the autocorrelation function (ACF) and partial autocorrelation function (PACF) used to guide order determination. In this context, p represents the non-seasonal autoregression order, d is the non-seasonal differencing, q represents the non-seasonal moving average order, P denotes for seasonal autoregression order, D is the seasonal differencing, Q represents the seasonal moving average order, and 's' indicates the length of the seasonal period. The best predictive model was identified based on the lowest Akaike Information Criterion (AIC), and its accuracy was further assessed using the root mean square error (RMSE) [19]. This approach aligns with standard practices in time series analysis [18], providing robust forecasting capabilities while accounting for seasonal variations in the data.

The fit of the model was validated for normality, homoscedasticity, and independence using quantile-quantile (Q-Q) plots, residual' distribution analysis, and the Ljung-Box test [20]. The chosen model was used to predict measles incidence in Nigeria for the year 2023, with the predictions visualized using a line chart. The mean absolute error (MAE) was computed to assess the average absolute difference between observed and predicted measles incidence for 2023. Furthermore, the model was extended to forecast monthly measles incidence from January 2024 to December 2026, providing a long-term projection of the disease to provide actionable insights for policymakers while balancing predictive reliability.

Results

3.1 Descriptive Analysis of Measles Incidence

The total number of measles cases reported from January 2011 to December 2022 was 203,587, and the average incidence was 7.5 cases per million population in Nigeria. The measles incidence ranged from 0.3 to 101.9 per one million population. Measles incidence peaked during January to March, with interquartile ranges of 13.5, 17.7, and 17.5 cases per one million population in January, February, and March, respectively, surpassing those of the other months (Figure 1). The highest spike was recorded in the year 2013, followed by 2019, and 2022 (Figure 2).

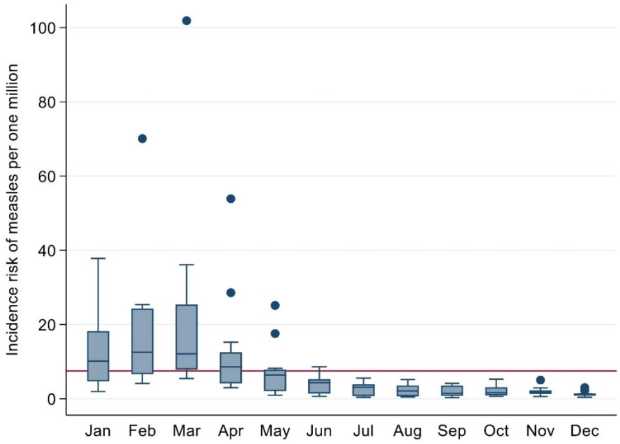

Figure 1. Box plot showing the distribution of the overall monthly incidence of measles per one million of the population in Nigeria (2011 to 2022), (red reference line depicts the overall average incidence)

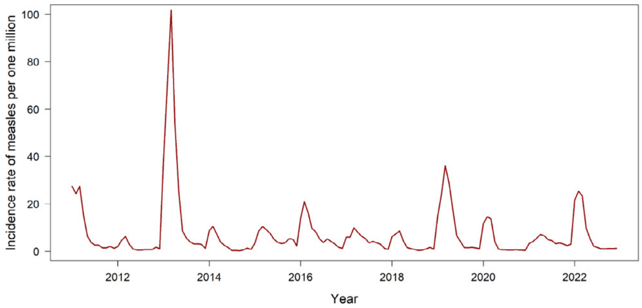

Figure 2. Line plot of the observed incidence of measles per one million population in Nigeria (2011 - 2022)

3.2 Seasonal ARIMA Model for 2012 to 2022

The STL decomposition analysis is broken down into four key components. The top panel displays the original time series, showing fluctuations in measles incidence with noticeable peaks and troughs. The second panel illustrates the seasonal component, highlighting a recurring annual pattern with consistent peaks and troughs, suggesting a distinct and stable seasonality in the incidence of measles. The third panel represents the long-term trend component, which does not exhibit a clear upward or downward trajectory, indicating no clear trend in the incidence of measles over the study period. Finally, the fourth panel captures the residual component, representing unexplained variation in the data after accounting for both seasonality and trend (Figure 3). The Durbin-Watson test indicated autocorrelation in the monthly time series data. After evaluating four SARIMA models using criteria such as AIC, ACF, PACF, and residual QQ-plot (Table 1), the SARIMA (3, 0, 1)(1, 1, 1)$_{12}$ model was chosen as the best-fitting model for predicting measles incidence in Nigeria.

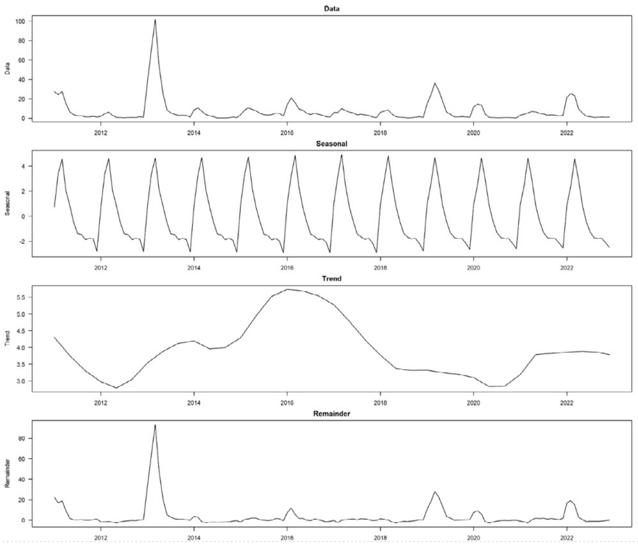

Figure 3. Seasonal and trend decomposition using Loess for incidence risks of measles per million population in Nigeria from 2011 to 2022

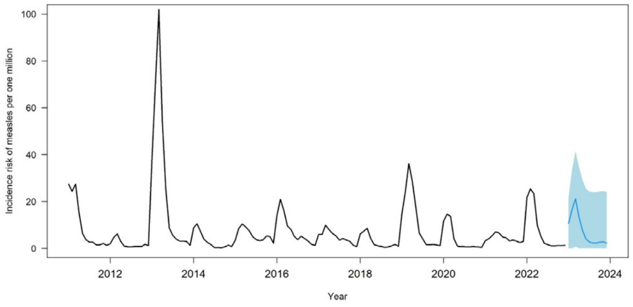

Figure 4: Time series of measles incidence per one million population in Nigeria with a 12-month forecast for 2023 and 95% prediction intervals

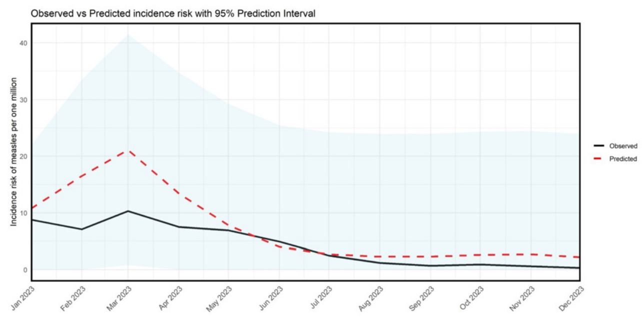

Figure 5. Line plot comparing the observed and predicted measles incidence with 95% prediction intervals per one million population in Nigeria for the year 2023

Table 1. The root mean square error and Akaike Information Criterion for the four fitted SARIMA models to explain the incidence of measles in Nigeria from 2011 to 2012

Fit	Models	Akaike Information Criterion	Root Mean Square Error
1	SARIMA(0,0,0)(0,1,0)$_{12}$	1137.8	17.1
2	SARIMA(0,0,0)(1,1,0)$_{12}$	1079.7	13.4
3	SARIMA(0,0,0)(1,1,1)$_{12}$	1034.9	10.4
4	SARIMA(3,0,1)(1,1,1)$_{12}$	867.6	5.3

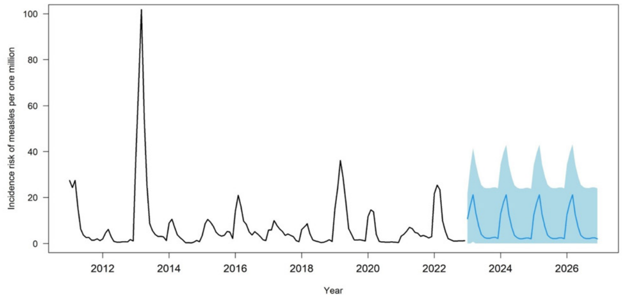

Figure 6. Time series showing the measles incidence per one million of the population in Nigeria, along with a 48-month forecast (2023–2026) and 95% prediction intervals

3.3 Forecasting the Measles Incidence to 2026

The SARIMA (3, 0, 1)(1, 1, 1)$_{12}$ model forecasted monthly measles incidence from January to December 2023 (Figure 4). A comparison between the predicted and observed data resulted in an MAE of 3.2 cases per one million population (Figure 5), and the observed incidence falls within the predicted estimates' 95% prediction interval for 2023. The model also projected similar measles incidence levels for an additional three years from January 2024 to December 2026 (Figure 6).

Discussion

Measles remains a major cause of child mortality in Nigeria and other developing nations, due to weak health infrastructure and vaccination coverage [4]. This study, employing time series analysis on eleven years of data from laboratory-confirmed measles cases, provides insights into the trends, seasonal patterns of measles incidence, and future projections of this trajectory.

In Nigeria, gaps in routine immunization campaigns have been a major factor contributing to recurrent measles outbreaks [21]. Despite a slight increase in vaccine coverage from 42% in 2012 to 47% in 2013, the country experienced its most extensive measles outbreak in 2013, particularly affecting unvaccinated children under five [21]. The outbreaks observed in 2019 and 2022 could likely be tied to a decline in vaccinations and were possibly exacerbated by the COVID-19 pandemic, as seen in other countries like the UK, the US, and Pakistan [22-24]. Adequate action is emphasized for Nigeria, citing low coverage, inadequate healthcare services, and limited community awareness as contributing factors [22, 25]. Measles remains endemic in Nigeria, as reflected in the country's consistently high case-reporting rates [21].

Since 2006, Nigeria has maintained a nationwide case-based surveillance system that includes identifying and reporting suspected cases, conducting serological confirmation, and sharing the data with the WHO on a weekly basis. In 2016 alone, Nigeria reported over 11,800 confirmed measles cases, accounting for nearly 40% of all confirmed cases reported in the African Region [21]. The study revealed endemic transmission, with measles incidence ranging from 0.3 to 101.9 per one million population, surpassing the WHO's control threshold of less than 5 cases per one million [4]. A clear seasonal peak was observed in measles incidence from January to March, with a gradual decline until December, consistent with findings from Ibrahim et al. [26]. This persistent transmission highlights the challenges in controlling measles in Nigeria and underscores the urgent need for sustained vaccination and public health measures to meet global health standards. Based on the observed seasonality, we recommend pre-emptive vaccination campaigns ahead of peak transmission periods to maximize immunity before cases surge. Additionally, targeted public health outreach efforts, such as awareness campaigns, school-based immunization programs, and enhanced surveillance, should be intensified during high-risk periods to mitigate outbreaks. These measures, informed by our results, could help optimize resource allocation and strengthen measles control efforts.

Statistical models play a crucial role in analyzing historical surveillance data, identifying patterns that may signal emerging health threats, and enabling timely responses from public health agencies to potential outbreaks [27]. ARIMA modeling, a popular technique for time series analysis and short-term forecasting, has found extensive application in epidemiology. It has been widely utilized to monitor and accurately predict infectious diseases, such as influenza in China and the USA, Leptospirosis in Thailand, and Cryptosporidiosis in Canada [28-30]. The application of the SARIMA model for predicting the incidence of measles is innovative. To the best of our understanding, no study has previously utilized this model in the surveillance of measles in Nigeria. This model incorporates the seasonality of measles and ensures stationarity before making predictions, offering enhanced reliability compared to the commonly used ARIMA model. In 2023, the predicted and observed measles incidence closely aligned with a moderate average absolute error. Extending the analysis, the model forecasts similar seasonal patterns and magnitudes persisting into 2026, contingent on constant factors. Ultimately, this study introduces a valuable tool for measles surveillance and prediction in Nigeria.

The predictions for measles incidence exhibit considerably wide 95% prediction intervals, with the intervals for each month including 0.00 cases per million population. Such wide CIs may result from unmeasured confounders in the data, such as variability in transmission dynamics, and or potential changes in vaccination coverage. While our model captures historical seasonality and trends, these findings underscore the importance of ongoing surveillance and adaptive public health strategies. Nigeria has implemented measures to control measles, including the integration of MCV1 and MCV2, but success hinges on addressing underlying challenges [21]. Proactive efforts are essential to prevent persistence of seasonal patterns in measles incidence. Contributing factors such as low vaccination coverage and delayed outbreak responses may sustain measles endemicity.

While our findings provide valuable insights to the monitoring and surveillance of measles incidence in Nigeria, several limitations should be acknowledged. First, the model predictions do not account for external factors such as vaccination campaigns, government interventions, or cross-border outbreaks, all of which can significantly influence measles transmission dynamics. As a result, the projections may be overly simplistic and should be interpreted with caution. Second, the study relies on case-based surveillance data, which may be subject to underreporting or misclassification, particularly in regions with limited healthcare access, such as Nigeria. Such data limitations could introduce bias in incidence estimates and impact the reliability of the forecasts. Additionally, this analysis focuses on the time series of measles in Nigeria, without considering its spatial component due to the absence of state-level data in the analyzed surveillance data. Furthermore, we approximated the estimated annual population of humans as the population at risk, which requires caution in the interpretation of the findings. This approximation may not fully reflect the true population at risk of the disease. Despite these constraints, our study highlights critical seasonal trends that can inform targeted public health interventions. Future research should integrate additional covariates to improve model robustness and predictive accuracy. Overall, this analysis provides a reference for decision-makers to formulate timely strategies for mitigating and eliminating measles in Nigeria. Emphasizing a targeted vaccination initiative in high-risk populations, particularly children, before the annual peak in March will ensure immunity and is crucial for effective outbreak prevention

Conclusion

This study identified a consistent seasonal peak in measles incidence from January to March in Nigeria, with no clear long-term trend observed. Forecasts suggest that these seasonal patterns and magnitudes will persist through 2026, underscoring the need for enhanced vaccination coverage and targeted interventions during peak seasons. However, the wide 95% prediction intervals around predicted estimates highlight uncertainty, emphasizing the need for ongoing surveillance. Therefore, policymakers are urged to implement the necessary measures to mitigate the anticipated increase in measles cases and work towards effective control and eventual eradication.

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Author contributions: RO: conceptualization, data analysis, validation, writing-original draft. BA: review of methodology, writing-review & editing. EJ and PA: writing-review & editing. OB: conceptualization, supervision, review, and editing.

Competing interests: None declared

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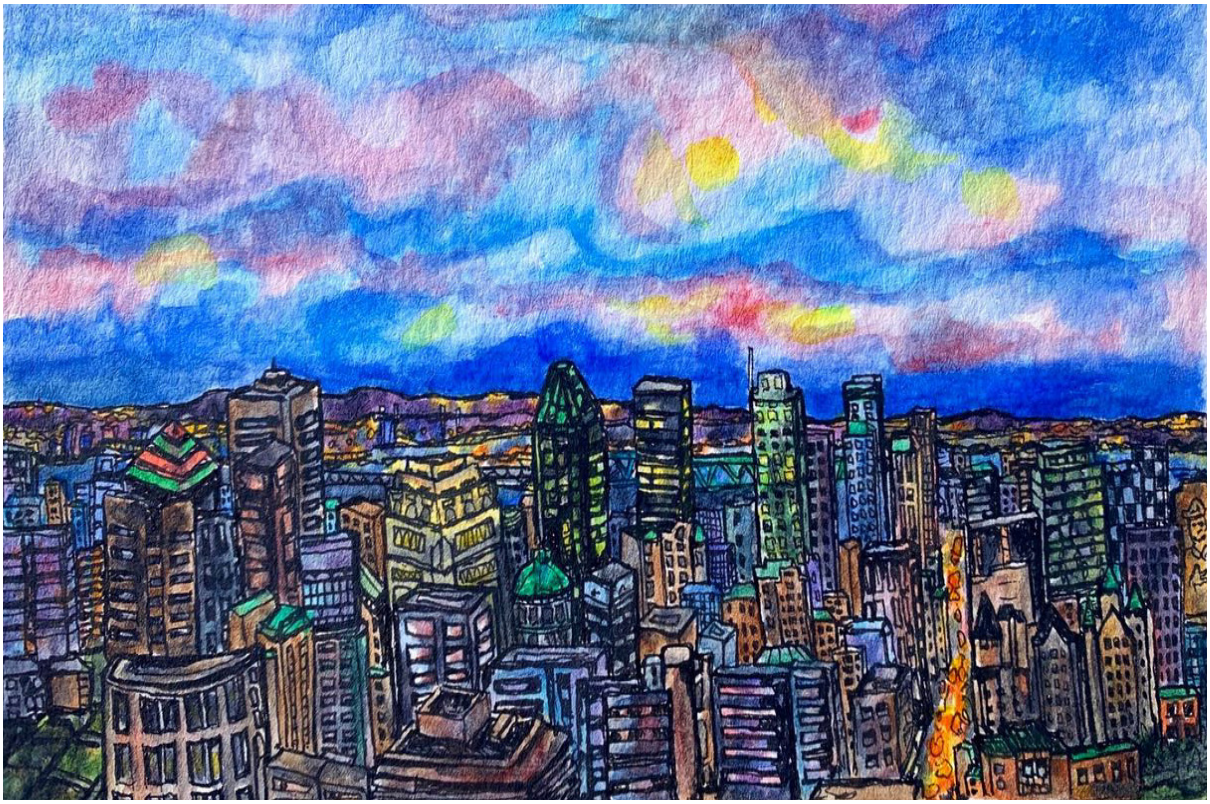

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