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ORIGINAL ARTICLE

A SARIMA time series forecasting for dengue cases for reporting to Yangon Region, Myanmar

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ABSTRACT

Dengue fever is a significant public health challenge in Myanmar, which requires accurate monitoring to mitigate its impact. The study aimed to develop a forecasting model for dengue cases in Myanmar's Yangon region using historical data from January 2002 to December 2022, with the objective of enhancing epidemiological surveillance and outbreak management. This retrospective observational study examines dengue cases in Yangon from January 2002 to December 2022, employing Seasonal Autoregressive Integrated Moving Average (SARIMA) models for predictive analysis. The most accurate model identified was SARIMA (2,0,1) $(1,1,1)_{12}$, with an AIC (Akaike Information Criterion) of 206.19 and MAPE (Mean Absolute Percentage Error) of 1.47%. According to the model, a peak in dengue cases was expected in July 2023, with an estimated 451 cases between January and December that year. Spatial variations in dengue incidence across Yangon's townships emphasize the need for targeted interventions. While the SARIMA model is valuable, it would also be important to consider many other risk factors like climate, migration patterns, virus characteristics, and socioecological factors to improve forecasting accuracy. These findings can aid public health policymakers in preventing and managing dengue outbreaks in Myanmar. However, additional research is needed to incorporate additional risk factors into the model to comprehensively understand dengue epidemiology and improve forecasting accuracy.

Key words:
dengue forecasting; SARIMA model; Yangon Region; epidemiological surveillance; outbreak prediction

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INTRODUCTION

Dengue is a viral infection that spreads from mosquitoes to people, and is more common in tropical and subtropical climates.[1] In 2023, approximately 3.6 billion people, comprising 40% of the world's population, reside in dengue-endemic areas, where an estimated 400 million individuals are infected with dengue virus annually, resulting in 100 million cases of illness and approximately 21,000 deaths.[2] The disease is now endemic in more than 100 countries in the WHO Regions, with the Americas, South-East Asia (SEA), and Western Pacific regions being the most seriously affected. Asia represents around 70% of the global disease burden.[1] Dengue cases in South and Southeast Asia are notably high, with a significant population of 1.3 billion residing in dengue-endemic areas across 10 countries in the SEA Region. Among the world's 30 most highly endemic countries, India, Indonesia, Myanmar, Sri Lanka, and Thailand are prominently included.[3] Dengue was first reported in Yangon in 1964, and a significant outbreak occurred in 1970, spreading to all other States and Regions in Myanmar.[4] Between 2012 and 2017, Myanmar reported 127,912 cases of dengue with 632 reported deaths, peaking in 2013, 2015, and 2017.[4] According to statistics obtained from the Ministry of Health (Myanmar), a total of 5,446 dengue cases and 36 deaths were reported in 2021. From January 1, 2022, to May 20, 2022, there have been 1,516 cases of the disease and 2 deaths reported in the Yangon Region. Notably, there is a significant number of cases in the Ayeyarwady Region and Mon State.[5] Undeniably, the Yangon Region continues to report the highest incidence of dengue in the country. Over time, dengue cases have spread to more townships, and the frequency of outbreaks has increased.[6]

An early warning system for dengue outbreaks has the potential to greatly improve the efficiency of vector control campaigns and allowing public health authorities to take proactive measures to prevent or control the spread of the disease.[7] Many mathematical models such as time series, compartmental models, agent-based models etc. have been developed to predict the occurrence, dynamics, and magnitude of dengue outbreaks. These models use a combined environmental and biological approach to forecast the risk of transmission and the potential magnitude of an outbreak. Moreover, they can integrate complex interactions between environmental and biological factors that influence dengue transmission.

Among them, time series analysis has been widely used and it can provide valuable insights into the temporal patterns of dengue transmission and the impact of environmental factors on the incidence of the disease.[8] One study conducted in Thailand used time series analysis to identify seasonal patterns and trends in dengue fever cases and provides valuable insights for disease prevention and control.[9] Another study conducted in Malaysia used time series analysis to develop an early warning system for dengue outbreaks by using a combination of environmental and meteorological data to develop a time series model and reported that the model had a high predictive accuracy, and could provide valuable information for targeted vector control interventions.[10] A study conducted in Brazil used time series analysis to investigate the relationship between temperature and dengue incidence.[11] These studies underscore the significance of time series analysis in advancing our understanding of dengue transmission dynamics and devising effective interventions to control the disease.

Time-series analysis is a valuable tool in public health and infectious disease surveillance.[12] In particular, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a time series modeling technique that has been widely used to predict and forecast data with seasonal patterns.[13] It has proven effective in modeling and forecasting dengue incidence, revealing temporal patterns and predicting future trends. SARIMA models are versatile and have numerous practical applications in dengue prevention and control. They can identify temporal patterns, guiding targeted vector control measures during high-risk periods. Moreover, SARIMA models help develop early warning systems for dengue outbreaks, enhancing vector control campaigns' efficiency and effectiveness.[14] This analysis offers insights into dengue transmission patterns and the impact of environmental and social factors on disease incidence.[15] For example, the utilization of trend analysis and SARIMA time series modeling has aided in comprehending temporal patterns and facilitating the development of enhanced prevention and control strategies in Gangetic West Bengal, India.[16] Similarly, SARIMA models have been applied worldwide, predicting dengue cases in regions like Brazil, Indonesia, and Myanmar.[17-19] While these studies have greatly advanced our understanding of dengue epidemiology, the current research distinguishes employing SARIMA modeling to forecast dengue cases, seeking to contribute novel insights specific to the unique dynamics of dengue transmission in Yangon, thereby aiding public health policymakers in more effectively preventing and managing dengue outbreaks in Myanmar. Time-series analysis is crucial for public health practitioners and researchers to understand the epidemiology and transmission dynamics of dengue, identify high-risk areas, and evaluate interventions. The aim of this study is to examine the spatial epidemiology of dengue incidence and predict the occurrence of dengue epidemics to help facilitate efficient dengue control in Myanmar.

MATERIAL AND METHODS

Study Design

A retrospective observational study was conducted using historical data on dengue cases in the Yangon Region, Myanmar, from January 2002 to December 2022.

Study area

The study area selected for this research is Yangon, the previous capital city of Myanmar, which is geographically located at 16°48' North and 96°09' East (16.8, 96.15). It covers an area of 598.75 km2 (231.18 sq mi). In 2023, the population of the Yangon region was 5,610,000, with a population density of approximately 12,308 individuals per square kilometer in the urban area of Yangon, making it the largest city in Myanmar.[20, 21] The region was chosen as the research area due to its significantly higher incidence of recorded dengue cases during the year 2002 compared to other states and regions of Myanmar.[22]

Data collection

The Vector Borne Disease Control Unit, Ministry of Health, Myanmar provided monthly data on dengue fever cases in Yangon Region from January 1, 2002, to December 31, 2022. Dengue is a notifiable disease in Myanmar, and all healthcare centers, including government and private institutions, are required to report any cases immediately to the Township Health Department. Dengue case surveillance, laboratory surveillance, and vector surveillance are integral components of the active surveillance system, with data being transferred to State and Regional Centers and the national VBDC program. In Myanmar, the standard case definition for dengue fever (DF), dengue hemorrhagic fever (DHF), and dengue shock syndrome (DSS) adheres to WHO guidelines, with confirmation of diagnoses primarily through serological and molecular methods.[23]

Data management and statistical analysis

An incidence map was created using GIS software such as ArcGIS (10.4.1) (ESRI, Redlands, California, USA) to visualize the distribution of dengue cases across the Yangon Region from 2013 to 2022. The process involved importing spatial data, creating a new layer, plotting dengue case data on the map, calculating incidence rates, and visualizing the data using graduated color or symbol maps.

The temporal patterns of dengue cases in Yangon were explored by plotting monthly cases. Various features of the data, including trends, seasonality, outliers, and smooth changes in structures, were evaluated using a graphical approach. Autoregressive integrated moving average (ARIMA) has been widely used for statistical modeling in time series analysis, and this approach was popularized by the Box and Jenkins models.[24, 25] Seasonal ARIMA (SARIMA) is an extended method utilized for analyzing time series data that demonstrates repetitive patterns over time. It is denoted as SARIMA (p,d,q) (P,D,Q)s, where p denotes the autoregression order, d represents the differencing order, q indicates the moving average order, P represents the seasonal autoregression order, D represents the seasonal differencing order, Q signifies the seasonal moving average order, and s denotes the length of the seasonal period.

In this study, we initially fitted a SARIMA (p,d,q) (P,D,Q)s model. To ensure stationarity, both seasonal and non-seasonal differencing techniques were applied to the dataset. Additionally, logarithmic transformation was utilized to adjust the data, aiming to achieve equal mean and variance within each period. The autocorrelation function (ACF) and partial autocorrelation function (PACF) were examined to determine the necessity of seasonal and non-stationary differencing. The model was fitted using a training dataset spanning from January 2002 to December 2022. Subsequently, the fitted model was validated using data from January 2022 to December 2022. We diagnosed a good model if the estimated parameters were significant with p-values < 0.05. For the model diagnostics, the Ljung-Box Q test was applied to ascertain whether the residual series represented white noise. The evaluation of the time series model included the use of the mean absolute percentage error (MAPE) and the Akaike Information Criteria (AIC). Lower values of normalized AIC were considered preferable. Once the best model was identified, we conducted forecasting for the year 2023.

The statistical analysis was conducted using R Studio software (version 2022.12.0+353, PBC, Boston, MA, USA, https://posit.co/). The analysis involved importing the data for preprocessing and cleaning. To perform time series modeling and forecasting, relevant R packages such as TSstudio, tseries (v0.10-47), zoo (v1.8-9), and forecast (v8.15) were utilized. All statistical tests and model diagnostics were carried out using built-in functions and custom scripts within the R Studio environment.

Ethical considerations

The study was approved by the Ethics Committee of the Faculty of Tropical Medicine, Mahidol University, Thailand (MUTM 2019-025-01) and the Defense Services Medical Research Centers, Myanmar (IRB/ 2018/ 26).

RESULTS

Figure 1. shows the map of the Yangon Region along with the incidence maps depicting the occurrence of dengue cases from 2013 to 2022. These maps highlight a significant incidence of dengue fever cases, especially during the rainy season (June – October), across all 44 townships of the region. In 2017, the highest recorded incidence surpassed 120 cases per 100,000 individuals. Notably, downtown areas and peri-urban areas reported incidences of 106 and 95.5 cases per 100,000 individuals in 2013 and 2015, respectively.

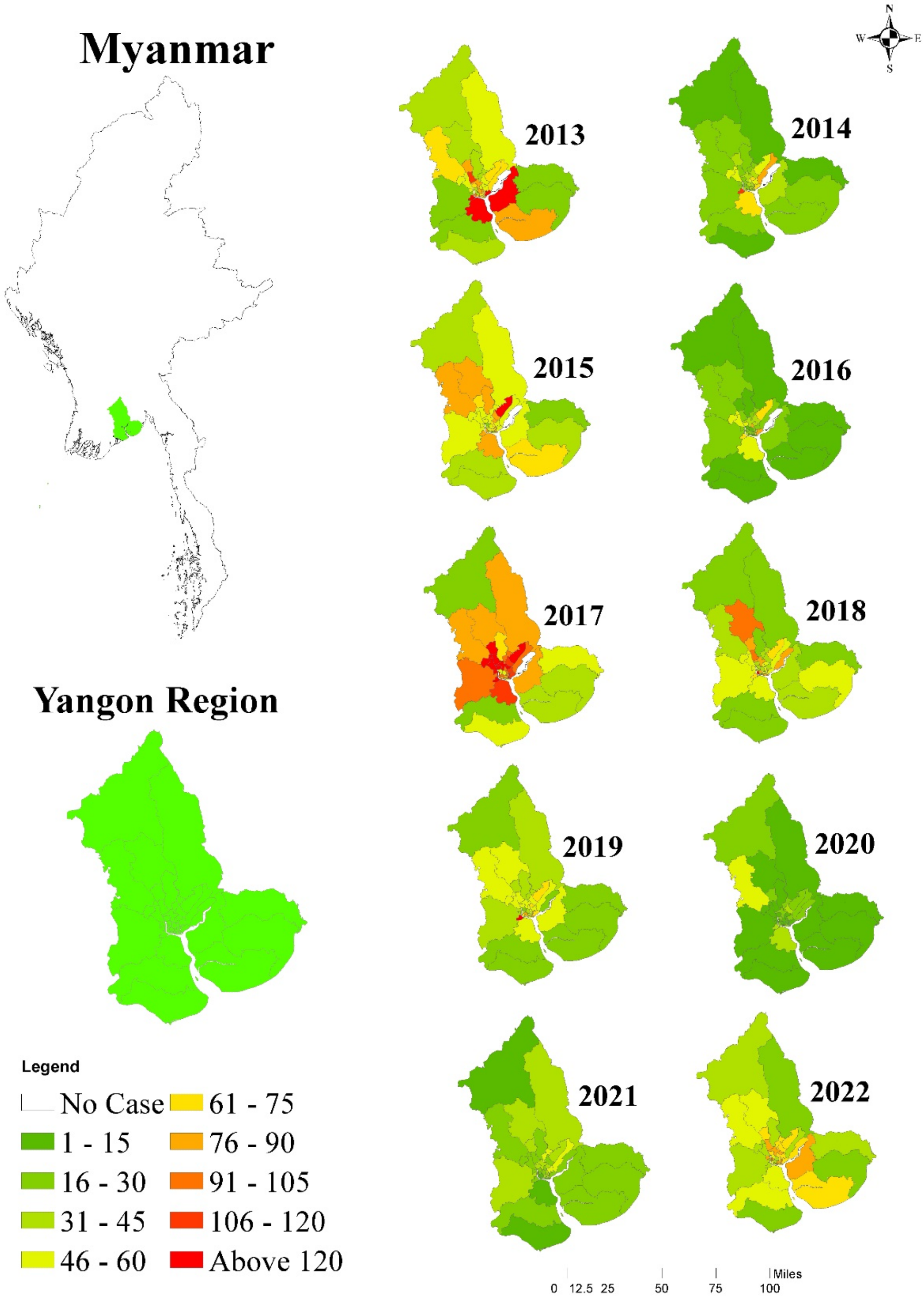

Figure 1 Map of the Yangon Region and the Dengue Incidence Map

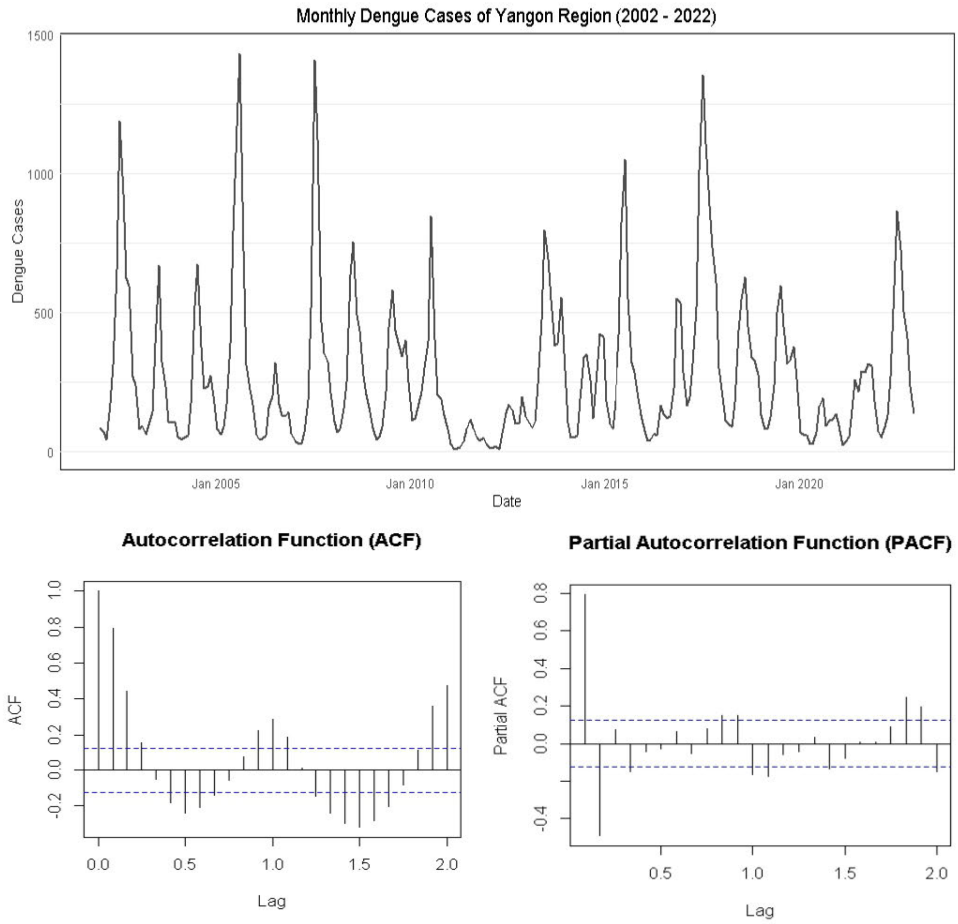

Figure 2 (a) Monthly number of dengue cases in the Yangon Region from January 2002 to December 2022 (Sources – VBDC, Ministry of Health) (b) Autocorrelation function (c) Partial autocorrelation function

Table 1. The Parameters of SARIMA (2,0,1) $(1,1,1)_{12}$ model

Variables	β	SE	P - value
AR (Lag 1)	-0.5994071	0.4762	0.0594
AR (Lag 2)	-0.08592521	0.0729	0.0575
MA (Lag 1)	0.49918239	0.4739	0.9082
AR, Seasonal (Lag 1)	-0.17644670	0.0827	< 0.001
MA, Seasonal (Lag 1)	-0.78593314	0.0674	< 0.001

AR = Autoregressive parameter, MA = Moving average parameter, AR (Seasonal) = Seasonal autoregressive parameter, MA (Seasonal) = Moving average parameter

This study utilized a training dataset consisting of monthly dengue cases in the Yangon Region from January 2002 to December 2022, demonstrating a seasonal pattern with a high peak during the rainy season (June-October). To ensure the data met equal mean and variance criteria for each period, a logarithmic transformation was applied. The observed series of monthly dengue cases displayed a non-stationary pattern with seasonal fluctuations, as displayed in Figure 2. To assess the stationarity of the data, the Dickey-Fuller test was conducted and indicated non-stationarity (P-value 0.01). Additionally, plots of the estimated autocorrelation function (ACF) and partial autocorrelation function (PACF) were generated using the training data, presented in panel (b) and (c) of Figure 2, respectively. The natural logarithm transformation was deemed the most suitable method for the data series. Table 1 summarizes the best-fitted models, highlighting the SARIMA (2,0,1) $(1,1,1)_{12}$ model. The coefficients (β), standard errors (SE), and p-values provide insights into model performance and parameter estimates. This systematic model selection process identified the suitable SARIMA (2,0,1) $(1,1,1)_{12}$ model, confirmed by statistical criteria and diagnostic assessments.

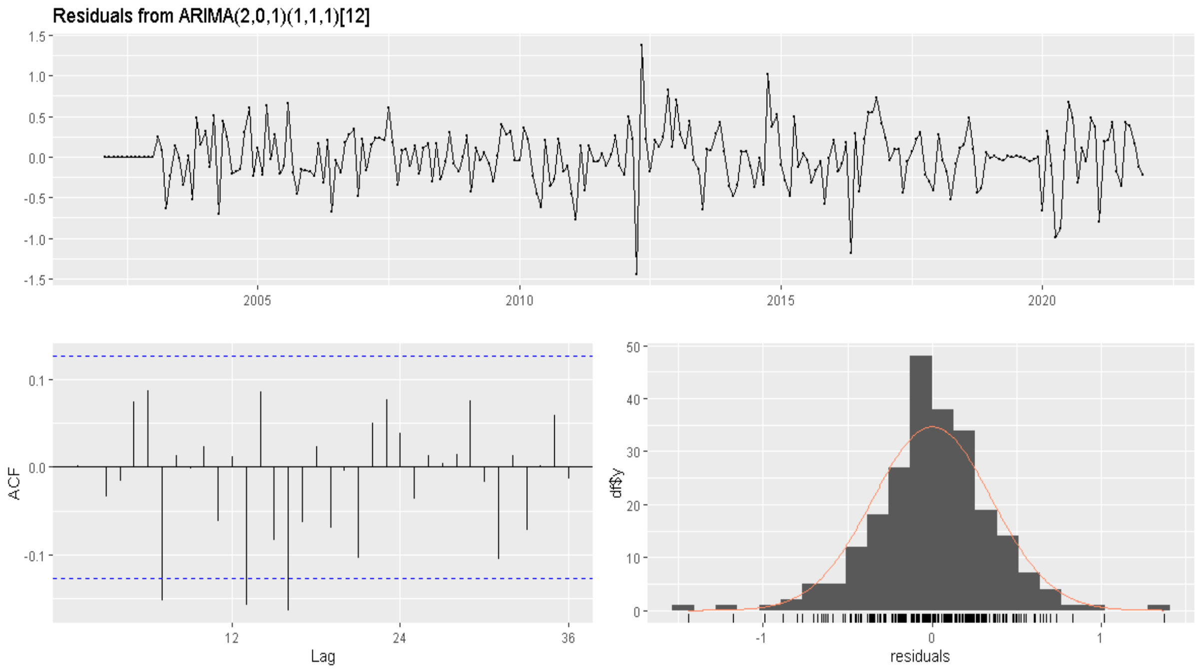

Figure 3. Graphical diagnostics for forecasting the SARIMA (2,0,1) (1,1,1)12 model (a. the standardized residuals b. ACF plot of residuals and c. histogram of the standardized residuals)

After estimating the model's parameters, we evaluated its adequacy by analyzing the residuals using several techniques, including standardized residuals, an ACF graph of the residuals, and a histogram (Figure 3). The ACF of the residuals in Panel (b) of Figure 3 indicates that the autocorrelations of the residuals are close to zero. The histogram in Panel (c) of Figure 3 demonstrates that the standardized residuals for the model closely approximate a normal distribution. Furthermore, the residuals ACF of the model were not showing statistically significant auto-correlation or white noise (Q = 29.015, p-value = 0.087), indicating the model is adequate. Based on these findings, we can conclude that the SARIMA (2,0,1) $(1,1,1)_{12}$ model provides an excellent fit for the data.

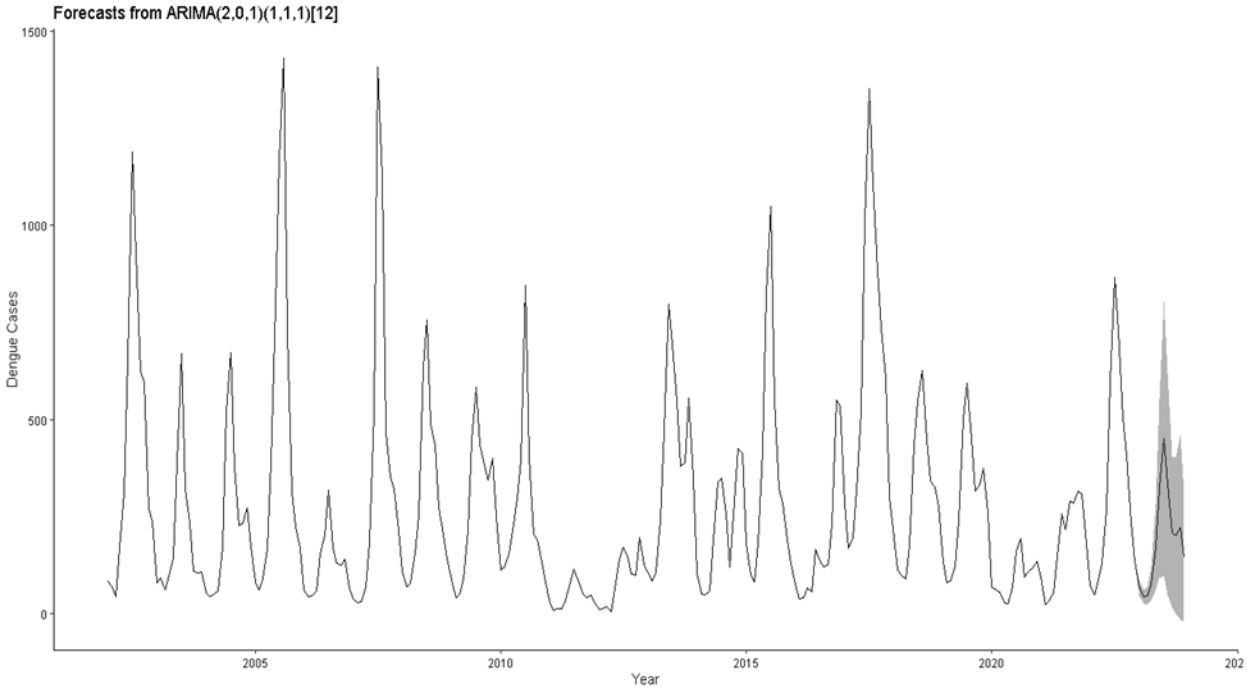

Figure 4. Observed number and predicted dengue from the SARIMA (2,0,1) $(1,1,1)_{12}$ model in 2023 in the Yangon Region

Table 2. Predicted dengue cases in the Yangon Region for 2023 derived from the SARIMA (2,0,1) $(1,1,1)_{12}$ model, after being converted from a logarithmic scale.

Year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2023	66.83	44.56	46.26	76.73	172.10	323.57	451.15	334.56	210.63	201.82	223.60	145.39

We utilized the SARIMA (2,0,1) $(1,1,1)_{12}$ model to forecast dengue cases from January to December 2023, as illustrated in Figure 4. The model's performance was assessed using the mean absolute percentage error (MAPE), which yielded a value of 1.47%. The observed and forecasted values of dengue cases for 2023 were presented in Figure 4, which showed that the SARIMA model accurately captured the data's trend and seasonality. The forecasted line closely followed the actual line, indicating that the model provided an acceptable fit for forecasting the number of dengue cases in 2023. The highest number of dengue cases was predicted to occur in July (451 cases).

DISCUSSION

In recent years, Dengue fever has emerged as a significant public health problem in Myanmar, with a rising number of cases. Although Dengue cases and deaths were reported across all fourteen States and Regions, Yangon had the highest percentage of total cases (17%). Additionally, the Yangon Region reported the most deaths in 2017, accounting for 31.3% of the annual total, with a Case Fatality Rate (CFR) of 0.8%.[4] The incidence of dengue is typically highest during the rainy season, affecting both urban and rural areas.[6] Myanmar has implemented a National Strategic Plan for

Dengue Prevention and Control, addressing the burden of dengue since 1960.[6] The Ministry of Health implements an active Vector-Borne Disease Control Program, emphasizing advocacy, preparedness, and seasonal monitoring.[26] Moreover, health promotion activities are regularly performed in schools to reduce the risk-taking behaviors related to dengue.[27] Forecasting, facilitated by techniques like SARIMA plays a crucial role in planning interventions and resource allocation [28]. This study utilized SARIMA to forecast dengue cases in Yangon, Myanmar, making it the first of its kind in the country. The findings serve as a valuable guide for officials and researchers in preparing for and responding to dengue outbreaks.

The accuracy of SARIMA forecasts is highly dependent on data quality and availability, as well as appropriate model parameter selection and assumptions. Therefore, thorough evaluation and validation of SARIMA models are crucial to ensure their reliability and usefulness in dengue forecasting.[29] In this study, non-stationarity in all data series was addressed by applying a log transformation. Seasonal differencing was performed to resolve the presence of a seasonal structure in dengue incidence data, as indicated by a seasonal lag. To determine the most suitable model for the entire Yangon Region from January 2002 to December 2022, identification, estimation, and diagnostic procedures were conducted. The results showed that a larger dataset yields better model fitting and forecasting accuracy than a smaller dataset. Notably, the order for seasonal components (P, D, Q) varied, and the best fit model for the Yangon Region was a SARIMA (2,0,1) $(1,1,1)_{12}$ model, which provided the most accurate forecasts of dengue cases.

Dengue remains a major health problem in Southeast Asia, particularly in Thailand, Vietnam, and the Philippines, where efforts are ongoing to manage outbreaks and enhance preventive measures.[30] Researchers in these countries have used SARIMA models to predict dengue cases effectively. For example, Bhatnagar *et al*. (2020) conducted a study in India and found that SARIMA models were helpful in predicting dengue fever and potential outbreaks of infectious diseases.[24] Similarly, Khaira *et al.* (2022) conducted research in Indonesia and showed that the SARIMA model accurately predicted monthly dengue cases, supporting early warning systems for dengue outbreaks.[31] In Brazil, Martinez *et al.* used a specific SARIMA (2,1,2)$(1,1,1)_{12}$ model to forecast dengue cases and suggested its usefulness in guiding public health policies.[18] In Malaysia, Jayaraj *et al.* (2019) analyzed monthly dengue data and discovered that the SARIMA model could predict potential dengue outbreaks up to four months in advance.[32] These studies demonstrate that SARIMA models have the potential to predict dengue cases in different settings. In Myanmar, forecasting models can assist in developing targeted strategies for preventing and controlling dengue, especially in areas with high predicted dengue rates. Integrating climate and meteorological data into these models can further improve their accuracy. Collaboration with other countries and sharing of best practices can contribute to enhancing dengue prevention and control efforts in Myanmar.

The findings of this study have significant implications for public health policy and practice in Myanmar, particularly concerning dengue. The use of forecasting models, specifically SARIMA (2,0,1) $(1,1,1)_{12}$, as demonstrated in this study, can provide essential information for targeted prevention and control strategies, including vector control measures, in areas where there is a high predicted incidence of dengue. The study predicts a monthly range of 44 - 451 dengue cases in the Yangon Region for 2023, with the peak transmission period expected from June to October. This finding is consistent with previous studies that indicate a lack of population immunity to different dengue serotypes.[18] Analysis of incidence maps for dengue fever in the Yangon Region from 2013 to 2022 reveals significant variations in incidence rates across the 44 townships. These findings align with similar studies conducted in Malaysia and Brazil, which identified higher incidence rates in specific regions due to variations in climate, socioeconomic status, urbanization, and vector control measures.[33, 34] Another study conducted in Thailand highlights the effectiveness of community-based intervention programs in reducing dengue incidence rates in high-risk areas.[35] Therefore, implementing effective vector control measures and public health interventions in high-risk areas, such as the Yangon Region, is crucial for reducing the burden of dengue fever.

The model's predictive power could be improved by considering the potential influence of climate factors, such as temperature, rainfall, and humidity on dengue transmission.[36] Incorporating these variables in future studies could enhance the model's predictive capabilities, aiding in the understanding of disease mechanisms and informing public health interventions and resource allocation. Despite the model's usefulness, several challenges exist in implementing effective dengue prevention and control measures in Myanmar. Limited resources and inadequate public health infrastructure could make it difficult to implement effective control and prevention strategies for dengue.[37] Additionally, social and cultural barriers could pose challenges in community engagement and awareness regarding the need for such control measures in dengue.[38]

Considering the limitations in this study, including the potential influence of climate factors, socioecological factors, and multiple risk factors is crucial when developing models to describe the pattern of dengue cases in future studies. Overall, the study's findings have significant implications for public health in Myanmar. Dengue prevention and control measures are critical to combat the disease's transmission during peak transmission seasons, and forecasting models can play a crucial role in informing such measures.

CONCLUSION

This study developed a Seasonal Autoregressive Integrated Moving Average (SARIMA) forecasting model for dengue cases in Myanmar's Yangon region, utilizing data from January 2002 to December 2022. The findings provide a valuable tool for regional health authorities to prepare for and respond to outbreaks. In this study, the SARIMA (2,0,1) $(1,1,1)_{12}$ model proved to be the most accurate. In addition, the model predicted a peak in dengue cases in July 2023 with an estimated 451 cases for 2023. The model is beneficial for epidemiological surveillance and policy makers in managing and preventing outbreaks of dengue fever. GIS maps revealed notable spatial variations in dengue incidence across Yangon’s 44 townships from 2013 to 2022, emphasizing the need for targeted interventions in high-risk areas for efficient vector control. Considering various different factors, including climate and socioecological elements, is crucial for accurately forecasting the incidence of a disease associated with multiple risk factors. Therefore, these factors should be considered when developing models to describe the pattern of dengue cases in future studies. The study recommends collaboration with other countries and continuing research to enhance Myanmar's dengue prevention efforts.

RECOMMENDATION

The study on dengue forecasting in Myanmar using SARIMA models provides valuable insights for improving disease surveillance and control. We recommend that Myanmar's health authorities use this accurate forecasting model to prepare for dengue outbreaks, which considers various risk factors. Collaboration with other countries and continued investment in data collection and research can further strengthen Myanmar's efforts in this regard. Overall, this study's findings can enhance strategies for preventing and managing dengue outbreaks in the country.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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