Environment and Natural Resources Journal
Volume 24
Issue 1
2026

Forecasting Dengue Fever Incidence in Thailand Using ARIMA: Implications for Public Health Planning

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ARTICLE INFO

Received: 19 Mar 2025
Received in revised: 5 Sep 2025
Accepted: 8 Sep 2025
Published online: 30 Oct 2025
DOI: 10.32526/ennrj/24/20250069

Keywords:
Dengue fever/ ARIMA Forecasting/ Time series analysis/ Public health/ Climatic factors

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ABSTRACT

Dengue fever remains a significant public health concern in Thailand, characterized by recurrent outbreaks and considerable morbidity. Understanding and forecasting temporal patterns of dengue incidence are essential for effective prevention and control strategies. This study analyzed monthly dengue fever incidence in Thailand from 2013 to 2024 and forecasted trends for 2025-2026 using the Autoregressive Integrated Moving Average (ARIMA) model. Data were obtained from the Bureau of Epidemiology, Department of Disease Control, and Ministry of Public Health. The optimal ARIMA (1,0,1) model was selected based on diagnostic criteria including the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and the Ljung-Box test. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE), yielding 43.40%, and indicating moderately accurate predictions for planning purposes. The model successfully captured seasonal trends, with dengue incidence typically peaking mid-year. Forecasts for 2025-2026 indicate periodic fluctuations, with December 2026 projected to have the highest incidence (7,336 cases) and January 2025 the lowest (2,401 cases). While the ARIMA model demonstrated utility in forecasting general trends, its limitations include the inability to incorporate external variables such as climate, vector control programs, vector control efforts, or viral serotype shifts. Despite this, the findings provide actionable insights for public health planning and resource allocation aimed at mitigating future dengue outbreaks in Thailand.

HIGHLIGHTS

ARIMA (1, 0, 1) was applied to forecast dengue incidence in Thailand. Twelve years of climate and case data enhanced the model accuracy. Seasonal peaks were detected, with December 2026 as the highest. Forecasts support timely dengue prevention and public health planning.

1. INTRODUCTION

Climate change has emerged as a critical global challenge, influencing all aspects of human life, including public health (Semenza et al., 2022; Wu and Huang, 2022) One of the most significant health consequences is the rise in vector-borne diseases, which have caused recurrent outbreaks across multiple regions (Delrieu et al., 2023). Among these, dengue virus (DENV) remains the most prevalent vector-borne viral infection worldwide, with the majority of cases concentrated in South America, Southeast Asia, and the Western Pacific (Guo et al., 2017). According to the World Health Organization (WHO, 2024), more than 12.7 million dengue cases were reported globally between January and September 2024 almost double the 6.5 million cases recorded in 2023. During this same period, dengue-related deaths totaled 8,791. Dengue is transmitted primarily by mosquitoes of the Aedes genus, notably *Aedes aegypti* and *Aedes albopictus*, which thrive in tropical and subtropical climates (Russo et al., 2020). These vectors are capable of spreading the virus even in the absence of clearly defined outbreak patterns, complicating control and prevention efforts.

Citation: Bunprom P, Siramaneerat I, Bhumkittipich P. Forecasting dengue fever incidence in Thailand using ARIMA: Implications for public health planning. Environ. Nat. Resour. J. 2026;24(1):88-97. (https://doi.org/10.32526/ennrj/24/20250069)

Thailand is among the countries most affected by dengue fever in Southeast Asia. Retrospective data from 2019 to 2024 indicate fluctuating but persistent disease transmission, with the most severe outbreak occurring in 2023, during which 158,620 cases and 181 deaths were reported (Thai PBS, 2023). Although the incidence declined to 105,250 cases and 90 deaths in 2024, the first quarter of 2025 still recorded 3,550 cases, a 4.8-fold decrease from the same period in 2024. Nevertheless, fatalities continue at an average rate of one death per week, indicating that dengue remains a persistent public health threat, particularly for children, the elderly, and individuals with obesity. Currently, no specific antiviral treatment or universally available vaccine exists for dengue infection. Patient management relies on immune system response and supportive care (WHO, 2025). This issue places a significant burden on the national healthcare system, particularly during epidemic periods (Wongkoon et al., 2012). Time series analysis is a critical methodological approach in public health and infectious disease surveillance, offering valuable insights into disease trends and outbreak dynamics (Sutriyawan et al., 2024). The Autoregressive Integrated Moving Average (ARIMA) model (Bayu et al., 2024) is a widely utilized time series forecasting technique for seasonal patterns and has been proven effective in modeling and predicting dengue fever incidence by identifying temporal patterns and forecasting future trends. With its high flexibility, the ARIMA model can be applied in various ways to prevent and control dengue fever, such as identifying temporal patterns to determine mosquito control measures during high-risk periods and aiding in the development of an early warning system for dengue outbreaks, thereby enhancing the efficiency and accuracy of vector control plans. Furthermore, time series analysis provides insights into dengue transmission patterns and the impact of environmental factors on disease incidence (Aung et al., 2024). The application of the ARIMA model has demonstrated success in various countries (Sutriyawan et al., 2024; Riley et al., 2020), underscoring its effectiveness in strengthening outbreak preparedness and public health interventions. Thus, this research aims to apply the Autoregressive Integrated Moving Average (ARIMA) time series model to forecast the incidence of dengue fever in Thailand. The ARIMA model was selected because it can effectively handle non-stationary time series data while providing transparent and interpretable results. Its practical applicability makes it well suited for public health decision-making, and previous studies in tropical settings have demonstrated its effectiveness in forecasting infectious disease incidence where seasonal patterns are dominant (Aung et al., 2024; Sutriyawan et al., 2024). The study focuses on identifying temporal patterns and predicting future trends, which will aid in the development of an early warning system and enhance mosquito control planning during high-risk periods. Furthermore, the findings will contribute to a deeper understanding of the transmission dynamics of dengue fever and the factors influencing disease outbreaks. The results of this study are expected to provide valuable insights for more effective prevention and control strategies for dengue fever in the future.

2. METHODOLOGY

2.1 Study design

This retrospective observational study was conducted using historical data from 2013 to 2024. The dataset included monthly time-series data on rainfall, relative humidity, minimum and maximum temperatures, and the number of rainy days, obtained from the Thai Meteorological Department. Corresponding dengue fever case data for the same period were sourced from the Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health.

2.2 Study area

Thailand covers an area of 513,120 square kilometers and is located between latitudes 5°37′N and 20°27′N and longitudes 97°22′E and 105°37′E (Government of Thailand, 2025). It is situated in the center of Southeast Asia, bordered by the Andaman Sea and the Gulf of Thailand (Figure 1) (Freepik, 2024). To the east, Thailand shares borders with Laos and Cambodia; to the north and west, it is bordered by Myanmar; and to the south, it borders Malaysia. The country is divided into six regions: Northern, Northeastern, Central, Eastern, Western, and Southern

Thailand, comprising 77 provinces with a total population of approximately 69 million people (Thai Meteorological Department, 2025). Thailand has a tropical climate, characterized by high temperatures and humidity. In general, the northern and northeastern regions experience lower temperatures than Bangkok in winter and higher temperatures in summer. The hottest months of the year are April and May. The rainy season extends from June to late October, while the period from November to late February is cooler and less humid. Thailand's climate is significantly influenced by monsoons, including the southwest monsoon, which brings moisture from the Indian Ocean during the rainy season, and the northeast monsoon, which carries cold, dry air from China during the winter season, as reported by the Digital Government Development Agency (DGA, 2025).

Figure 1. Map of Thailand

2.3 Statistical analysis

Data analysis was conducted using Gretl version 2023d, an open-source econometric software. The temporal pattern of dengue incidence in Thailand was analyzed using the Autoregressive Integrated Moving Average (ARIMA) model, following the Box-Jenkins methodology (Abhinandithe and Vaishnavi, 2019). Monthly dengue incidence data from 2013 to 2024 were used to build the time series model.

To verify stationarity, both the Augmented Dickey-Fuller (ADF) and KPSS tests were applied to the original series. The ADF test failed to reject the null hypothesis of non-stationarity, while the KPSS test indicated non-stationarity as well. Consequently, first-order differencing (d=1) was applied, after which the series achieved stationarity. Candidate autoregressive (p) and moving average (q) terms were then identified by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, supplemented by Gretl's automatic model selection procedure with a periodicity of 12.

Several ARIMA specifications were estimated and compared using the Akaike Information Criterion (AIC), where lower values indicate a superior fit. Among the candidate models tested, including ARIMA (1,0,0), ARIMA (1,0,1), and ARIMA (13,0,0) the ARIMA (1,0,1) model achieved the lowest AIC value, representing the best balance between explanatory power and parsimony. Table 1 shows the comparison of ARIMA model specifications, including log-likelihood and AIC values. Among the candidate models, ARIMA (1,0,1) achieved the lowest AIC, confirming its suitability as the best-fitting model.

Table 1. Comparison of candidate ARIMA models for dengue incidence forecasting in Thailand (2013-2024)

Candidate model	p	d	q	Log-lik(L)	AIC
ARIMA (1,0,1) (selected)	1	0	1	-1,355.031	2,718.062
ARIMA (1,0,0)	1	0	0	-1,375.651	2,719.727
ARIMA (13,0,0)	13	0	0	-1,375.651	2,757.301

Residual diagnostics confirmed the adequacy of the selected model. The residual ACF and PACF remained within the 95% confidence bounds, the Ljung-Box test showed no evidence of serial correlation, and the stationary R2R^2R2 value indicated a strong fit. Residuals were normally distributed, independent, and homoscedastic, thereby meeting the assumptions of the ARIMA framework.

Finally, the ARIMA (1,0,1) model was used to generate 24-month forecasts of dengue incidence for 2025-2026. Forecast accuracy was evaluated using the Mean Absolute Percentage Error (MAPE), and 95% prediction intervals were constructed to reflect forecast uncertainty.

2.4 Ethical consideration

Ethical approval for the study protocol was obtained from the Ethics Committee of Sirindhorn College of Public Health, Yala having the approval number SCPHYLIRB-2567/452 period. All the information obtained was anonymized, and data privacy and confidentiality were ensured (IRB/16 Dec/2024).

3. RESULTS

Figure 2 presents a map of Thailand along with a spatial representation of the dengue incidence rate from 2013 to 2024. This map illustrates the spread of dengue fever across all 77 provinces, revealing a cyclical pattern of outbreaks. Based on monthly dengue case data in Thailand from 2013 to 2024 (a total of 144 months), the findings indicate that dengue outbreaks exhibit a recurring cycle, with cases typically peaking in the mid-year period (May-September) and declining towards the end of the year (November-February). This pattern aligns with the rainy season and temperature fluctuations that influence the breeding of Aedes mosquitoes. The highest number of monthly cases recorded was 31,132, particularly during severe outbreak years such as 2015, 2019, and 2022. In contrast, the lowest number of cases observed was 391, which occurred during the winter months. This decrease may have been influenced by disease control measures, particularly during 2020-2021, when COVID-19 lockdown policies were implemented (Liyanage et al., 2021). Additionally, the data reflect an epidemic cycle occurring every 3-4 years, a distinctive characteristic of dengue outbreaks in Thailand. This study utilizes a dataset comprising monthly dengue case records in Thailand from January 2013 to December 2024, revealing that the data exhibit a random or non-seasonal pattern. The time series of dengue cases observed demonstrates a stationary pattern, as depicted in Figure 3(a).

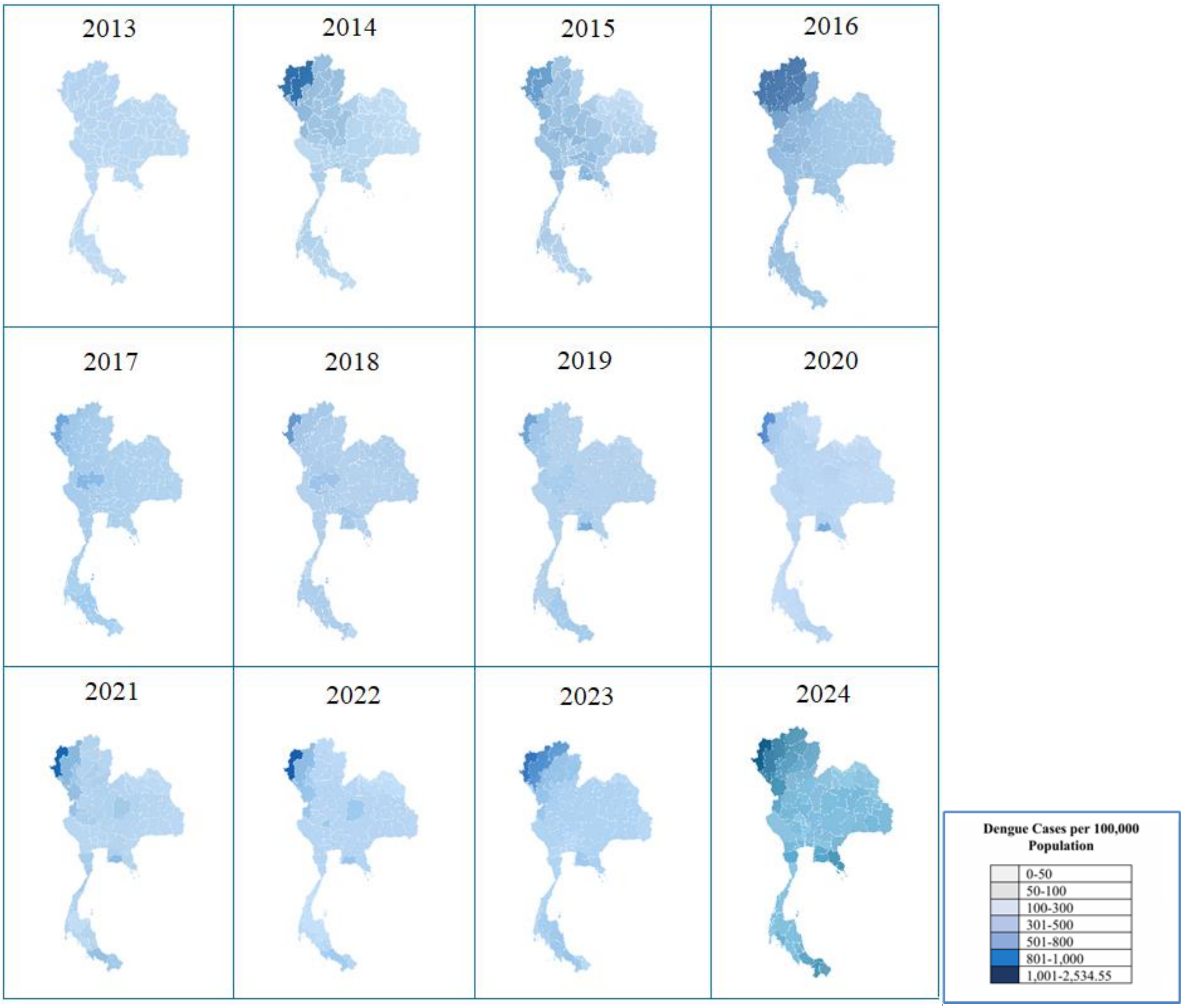

Figure 2. Dengue incidence in Thailand in 2013-2024

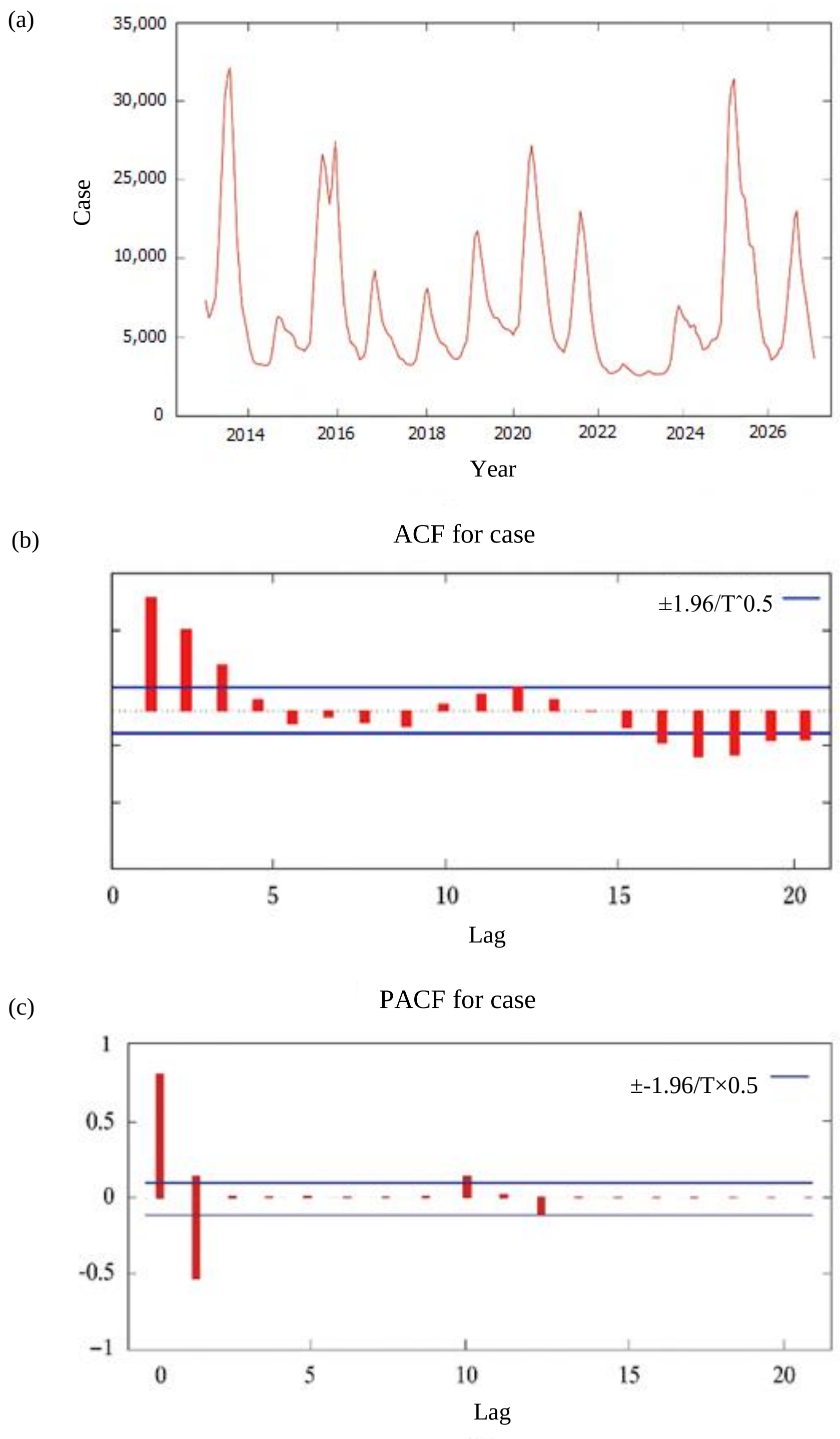

Figure 3. Dengue incidence from January 2013 to December 2024 in Thailand (a), autocorrelation function (b), partial autocorrelation function (c).

The automatic model selection in Gretl identified periodicity of 12 for the selected data. The ARIMA (1,0,1) model was identified as the best fitting model for the given data, providing predictive values for a 12-month forecast from January 2013 to December 2024. The difference between the observed value and the predictive value for each month was referred to as the residual of the model. The Autocorrelation factor (ACF) and The Partial autocorrelation factor (PACF) were tested for residuals to observe the pattern of residuals. Residuals should not show any significant pattern, only then will the selected model be considered as best fitting model.

As shown in Figure 3, the auto correlation and the Partial auto correlation of predicted cases at different lag times are depicted. Two lines in the graph indicate the 95% confidence limits of the residual ACF and residual PACF. At any lag time, the residual ACF and residual PACF did not exceed the 95% confidence limits indicating that there were no significant autocorrelation patterns between the residuals across different lag times. This suggests that the residuals exhibited no significant pattern and were discrete, independent and identically distributed following a white noise pattern. Table 1 presents the model fit statistics and Ljung-Box test for residuals of the selected predictive model (seasonal ARIMA (1,0,1)). The model yielded a stationary R-squared value of 0.8576. The Ljung-Box test statistic was 11.271, with a p-value of 0.792, indicating that the residuals were not significantly autocorrelated and confirming the adequacy of the selected model.

Moreover, the findings of this study reveal a seasonal trend that is generally consistent with historical dengue incidence, although the projected peak month differs, indicating that the model is sufficiently suitable for forecasting dengue incidence rates for 2025-2026. The ARIMA (1,0,1) model was applied to predict the incidence rate of dengue fever from January 2025 to December 2026, yielding a Mean Absolute Percentage Error (MAPE) of 43.40%. The forecasted incidence rates for dengue fever in 2025-2026 are presented in Figure 4, which illustrates that the trend of dengue cases in Thailand from January to December 2025-2026 shows periodic increases, along with fluctuations in case numbers and a 95% confidence interval (95% CI) surrounding the projections.

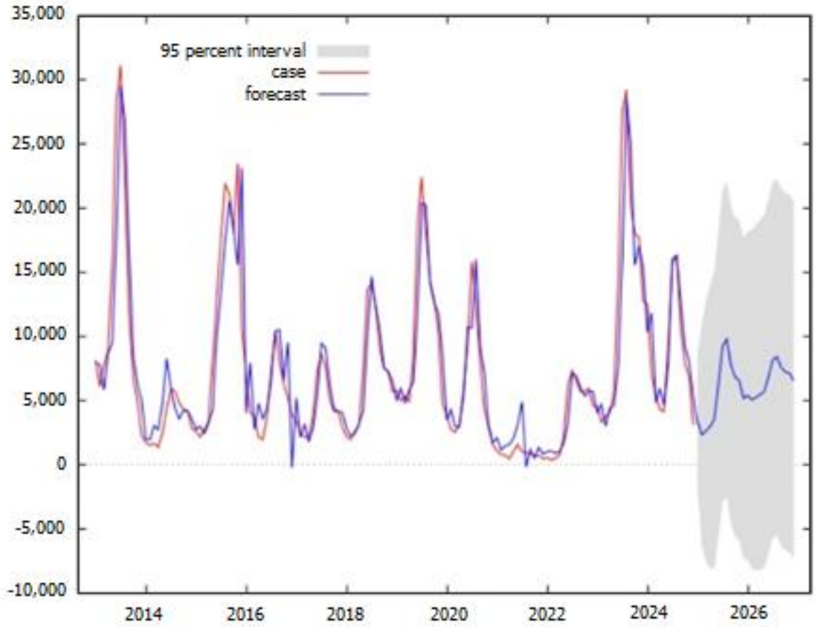

Figure 4. Observed and predicted dengue incidence from ARIMA model (1, 0, 1) in 2025-2026 in Thailand

Furthermore, the forecasted incidence of dengue fever in Thailand during 2025-2026, as presented in Table 2 and Figure 4, indicates clear seasonal patterns. The model projects that December 2026 will record the highest number of cases (7,336 cases), while January 2025 is expected to have the lowest incidence (2,401 cases). These findings were generated using the ARIMA (1,0,1) model, which successfully captured temporal fluctuations in dengue transmission. Notably, the predicted monthly values show a consistent upward trend throughout the forecast period, with case numbers rising steadily across consecutive months. This suggests an intensification in disease transmission, warranting enhanced vector-control and preparedness efforts.

4. DISCUSSION

Over the past decade, dengue fever has continued to pose a complex public health challenge in Thailand, with seasonal outbreaks and varying intensities across regions. By employing the ARIMA (1,0,1) model to forecast dengue incidence from 2025 to 2026, this study offers a valuable analytical lens into future trends based on historical disease patterns. The model, built upon 12 years of surveillance data, captured cyclical fluctuations consistent with monsoon-driven mosquito breeding and revealed a projected case peak in December 2026, suggesting a possible extension of transmission beyond the traditional rainy season. These findings align with prior work in similar tropical settings, such as Indonesia and Vietnam, where ARIMA models have informed early detection systems and resource allocation strategies (Olowe et al., 2023; Zaw et al., 2023).

Table 2. Monthly predicted dengue fever cases in Thailand during 2025-2026 based on the ARIMA (1, 0, 1) model

Month (2025)	Cases	Month (2025)	Cases
January	2,401	January	7,152
February	3,570	February	7,198
March	4,462	March	7,233
April	5,144	April	7,260
May	5,665	May	7,280
June	6,062	June	7,296
July	6,366	July	7,308
August	6,598	August	7,317
September	6,775	September	7,324
October	6,910	October	7,329
November	7,013	November	7,333
December	7,092	December	7,336

One of the study's notable contributions lies in its integration of long-term national data, which enhances forecasting reliability and policy relevance. In practical terms, identifying periods of heightened risk supports the development of more timely, targeted vector-control operations. The potential shift in seasonal peaks underscores the need to reevaluate current prevention strategies, which have historically concentrated on mid-year interventions. Strengthening surveillance efforts in the months leading to the projected December spike could mitigate the burden of outbreaks, particularly in densely populated or resource-constrained settings. These insights are not merely statistical; they provide actionable guidance for operational planning, health worker mobilization, and community engagement.

Despite these contributions, the ARIMA model's simplicity, while a strength in terms of transparency and accessibility, also introduces notable limitations. The exclusion of exogenous variables such as precipitation, temperature, or other socio-environmental conditions restricts the model's ability to fully capture the multifactorial nature of dengue transmission. By applying ARIMA (1, 0, 1), however, the model captures cyclical trends that may reflect monsoon-driven mosquito dynamics, thereby offering partial insights into seasonal patterns despite its restricted scope. Moreover, unaccounted factors such as vector-control effort, virus serotype shifts, and changes in human mobility patterns may influence outbreak dynamics in ways not reflected in historical case data. While the model's mean absolute percentage error (MAPE) was moderate, the absence of external inputs may hinder its responsiveness to atypical outbreak scenarios. To address these limitations, future research should explore ARIMAX or SARIMAX models that integrate climatic variables, as well as nonlinear approaches such as long short-term memory (LSTM) networks and ensemble machine learning models for greater precision (Ouattara et al., 2022; Wibawa et al., 2024).

This study's findings are also situated within the broader context of climate-sensitive disease surveillance. As climate patterns become more erratic, disease forecasting must evolve beyond historical extrapolation. The increasing unpredictability of dengue trends reinforces the need for adaptive, multi-sectoral strategies. Framing these results within the social-ecological systems (SES) framework helps underscore the interdependence between human behavior, ecological changes, and vector dynamics (Watts et al., 2020). Furthermore, this research contributes to global health agendas by aligning with Sustainable Development Goal (SDG) 3 on ensuring healthy lives, and SDG 13 on climate action. By advocating for climate-informed vector control and data-driven early warning systems, the study offers both scientific and strategic value.

In summary, while the ARIMA (1,0,1) model has clear limitations in isolating the drivers of dengue outbreaks, it remains a practical tool for trend estimation and risk anticipation. Its utility lies not only in what it predicts but in how those predictions can shape preparedness. Building upon these results with more integrative models will allow public health authorities to respond more effectively to a changing epidemiological landscape. In the long term, embedding predictive analytics into routine disease surveillance can serve as a cornerstone of Thailand's broader climate resilience and public health readiness. This aligns directly with the study's objectives, as outlined in the introduction, which emphasize identifying temporal patterns and predicting future trends. By achieving these aims, the research provides a foundation for developing an early warning system and strengthening mosquito control planning during high-risk periods.

4.1 Interpretation of key findings

This study reveals a recurring pattern in dengue fever outbreaks in Thailand, with the highest incidence observed during the rainy season (May-September), driven by climatic conditions such as rainfall and temperature fluctuations that favor mosquito breeding. The cyclical nature of the outbreaks, with peaks every 3-4 years, highlights the influence of environmental factors on dengue transmission. Notably, the ARIMA model identified significant seasonal fluctuations, providing a strong foundation for forecasting future outbreaks. Furthermore, the ability of the ARIMA model to capture recurrent seasonal peaks demonstrates its utility as a practical forecasting tool for dengue fever in Thailand. Unlike simple trend analysis, ARIMA accounts for both short-term autocorrelations and long-term seasonal cycles, providing reliable short-term forecasts that are critical for planning vector control operations. This adaptability to historical surveillance data, combined with its relatively low data requirements, makes ARIMA particularly advantageous in resource-limited settings where more sophisticated models may not be feasible. For example, Mustaffa and Zahari (2024) found that seasonal ARIMA models performed competitively against more complex models in forecasting dengue incidence in Malaysia, reinforcing ARIMA's practical utility in tropical public health contexts. However, while the model performed well in capturing the trends, the study's relatively low explanatory power suggests that factors beyond climate, such as socio-economic conditions, vector control measures, and urbanization, also play significant roles in the transmission dynamics.

4.2 Public health implications

The study's findings have important implications for public health strategies in Thailand. First, the predictable seasonal pattern of dengue outbreaks provides an opportunity for targeted interventions during peak transmission periods. This includes intensified vector-control efforts, such as mosquito spraying and habitat elimination, particularly during the rainy season. Additionally, early warning systems that integrate real-time weather data can help health authorities take proactive measures before an outbreak reaches its peak, potentially reducing the burden on healthcare systems. Furthermore, the study's emphasis on the cyclical nature of outbreaks calls for sustained and long-term planning rather than reactive, short-term responses. Strengthening surveillance systems, especially in rural and peri-urban areas, will also be crucial in detecting and responding to early signs of dengue resurgence.

4.3 Novel contributions of the study

This study makes several novel contributions to the field of dengue epidemiology. First, it offers a detailed, long-term analysis (2013-2024) of dengue incidence in Thailand, using a comprehensive dataset that includes both climatic and disease data. The study's integration of the ARIMA model for forecasting dengue outbreaks based on climatic variables provides a robust statistical approach to understanding dengue dynamics. The research also identifies the specific climatic factors (temperature and rainfall) most strongly associated with dengue transmission in Thailand, which can inform localized prevention strategies. Additionally, the study's focus on seasonal fluctuations in disease incidence contributes to understanding how climate variability influences the frequency and severity of outbreaks across regions.

Rather than reiterating the results, the discussion has been restructured to emphasize the insights drawn from the findings. While the ARIMA model's effectiveness is acknowledged, the key takeaway is the broader public health implications, particularly the importance of integrating climate-sensitive approaches into dengue control programs. More directly, these findings highlight how evidence-based forecasting can guide targeted interventions and shape policy decisions to improve dengue preparedness and prevention. The novel contribution lies in linking climatic variability with seasonal outbreaks, which can now be used to inform early warning systems and strengthen disease surveillance. The limitations section highlights areas for further research, including the need to account for additional variables such as socio-economic and environmental factors, which will enhance the predictive capacity of future models.

5. CONCLUSION

This study presents an ARIMA model for forecasting the incidence of dengue fever in Thailand, utilizing monthly confirmed dengue case data from 2013 to 2024. The analysis indicates that the ARIMA (1,0,1) model was identified as the best-fit model, as it accurately described the data and demonstrated the ability to forecast dengue incidence. The evaluation of the forecast revealed a Mean Absolute Percentage

Error (MAPE) of 43.40%, indicating that the model provided reasonably accurate predictions. The forecast for 2025-2026 shows that December 2026 is expected to have the highest number of dengue cases, reaching 7,336, while January 2025 is predicted to have the lowest at 2,401 cases. These findings provide valuable insights for future dengue control and prevention efforts.

While the findings of this study provide valuable insights into the seasonal trends of dengue fever in Thailand, further research is needed to address the limitations outlined above. Public health authorities can benefit from this study by using the model's forecast to prepare for expected outbreaks, particularly in the high-risk months. However, incorporating additional variables and exploring more advanced forecasting techniques will allow for more accurate predictions, ultimately improving response strategies. Future research should focus on the integration of diverse data sources, including socio-economic and environmental factors, and adopting machine learning methods to enhance the precision and adaptability of dengue forecasting models.

6. LIMITATIONS

This study has several limitations that must be considered when interpreting the findings. First, the exclusion of exogenous variables, such as climatic and environmental factors beyond temperature, humidity, and rainfall, may have impacted the model's predictive power. Factors like urbanization, land use changes, and public health interventions (e.g., vector control measures) are known to influence dengue transmission dynamics and should be incorporated into future studies for a more comprehensive understanding. Additionally, underreporting or misclassification of dengue cases, particularly in rural or resource-limited settings, could lead to inaccuracies in the data, potentially skewing the results. This issue is particularly relevant in regions with limited access to healthcare or surveillance infrastructure, where dengue cases may not be accurately recorded.

Furthermore, the reliance solely on the ARIMA model presents another limitation. While effective in modeling linear trends, the ARIMA model may not fully capture the complex, non-linear dynamics of dengue outbreaks, particularly during periods of sudden surges or atypical conditions. As a result, the model's ability to predict extreme outbreak conditions is constrained. Future studies should consider integrating climatic data into more robust multivariate models, such as ARIMAX or SARIMAX, which can incorporate additional exogenous variables for more accurate forecasting. Additionally, alternative or complementary forecasting methods, such as machine learning techniques (e.g., random forests, gradient boosting, and Long Short-Term Memory (LSTM) neural networks), could offer improved modeling of non-linear relationships and better handle complex patterns. Hybrid models that combine statistical methods with machine learning techniques may also enhance forecast accuracy and reliability, particularly during atypical outbreak conditions.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the faculty members of the Environmental Social Sciences and Sustainable Development Program, Faculty of Liberal Arts, Rajamangala University of Technology Thanyaburi (RMUTT), for their invaluable guidance, encouragement, and academic support throughout this research.

AUTHOR CONTRIBUTIONS

Punpaphat Bunprom conceptualized and drafted the manuscript, as well as interpreted the analyses; Issara Siramaneerat provided guidance on the data analysis, reviewed and approved it; Pimnapat Bhumkittipich assisted in studying the qualitative results. All authors have reviewed and approved the manuscript.

DECLARATION OF CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

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