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Анализ временны́х рядов заболеваемости денге в городе Бандунг, Индонезия, с использованием модели ARIMA

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Аннотация
Введение. Вирус денге является проблемой общественного здравоохранения, которая приводит к смерти. Это заболевание необходимо контролировать, чтобы уменьшить его воздействие на общество.
Цель исследования — спрогнозировать заболеваемость денге в городе Бандунг, используя данные с 2014 по 2023 г.
Метод. В данном исследовании изучалась заболеваемость денге в городе Бандунг с 2014 по 2023 г., вторичные данные обрабатывали и анализировали с помощью модели авторегрессии скользящего среднего (ARIMA) для прогнозирования заболеваемости денге.
Результаты. Лучшей моделью является ARIMA (3,0,3), средняя абсолютная ошибка в процентах (MAPE = 33,3437) и информационный критерий Акаике (AIC = 0,1489). Исходя из модели, пик заболеваемости денге приходится на сентябрь 2024 г. (320 случаев).
Выводы. Пик заболеваемости денге в городе Бандунг придётся на сентябрь 2024 г. Отсюда следует, что необходимо проводить мероприятия по борьбе с переносчиками инфекции в нескольких подрайонах и наращивать усилия по профилактике и борьбе с денге.

Ключевые слова: *заболеваемость денге, прогноз заболеваемости денге, модель ARIMA, прогноз вспышек, Индонезия*

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Источник финансирования. Авторы заявляют об отсутствии внешнего финансирования при проведении исследования.

Конфликт интересов. Авторы декларируют отсутствие явных и потенциальных конфликтов интересов, связанных с публикацией настоящей статьи.

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Time series analysis of dengue incidence in Bandung City, Indonesia using a ARIMA model

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Abstract
Background. Dengue is a public health problem that leads to death. This disease is necessary to monitor to reduce its impact on the community.
Purpose. This study aims to forecast the incidence of dengue in Bandung City using historical data from 2014 to 2023.
Method. This retrospective observational study examined dengue incidence in Bandung City from 2014 to 2023, secondary data were processed and analysed using Autoregressive Integrated Moving Average (ARIMA) model to forecast dengue incidence.
Results. The best model generated is ARIMA (3,0,3), Mean Absolute Percentage Error (MAPE = 33,3437) and Akaike Information Criterion (AIC = 0,1489). Based on the model, the peak of dengue cases is estimated to occur in September 2024 (320 cases).
Conclusion. The peak incidence of dengue in Bandung City will occur in September 2024. Hence the need for vector control efforts in several sub-districts and increasing efforts to prevent and control dengue.

Keywords: *Dengue incidence, Dengue forecast, ARIMA model, outbreak prediction, Indonesia*

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Introduction

Dengue is a disease transmitted by the Aedes aegypti and Aedes albopictus mosquitoes, caused by the dengue virus. It is more common in tropical and subtropical climates[1]. In 2013, approximately 3.6 billion people and 40% of the global population resided in areas at risk of dengue or endemic to the disease. It is estimated that 400 million individuals contracted the dengue virus annually, resulting in 100 million dengue cases and approximately 21,000 deaths[2]. A total of more than 100 countries worldwide have been identified as being endemic to dengue. The Americas, Southeast Asia and the Western Pacific are the most severely affected regions by this disease. Seventy percent of the disease burden is concentrated in Asia. South and Southeast Asia are the regions with the highest number of cases, with an estimated 1.3 billion people residing in dengue-endemic areas across 10 countries in Southeast Asia. Among the 30 countries with the highest endemicity rate in the world, India, Indonesia, Myanmar, Sri Lanka and Thailand are included[3]. Indonesia is one of the countries contributing the most cases of dengue in the world, with the number of cases continuing to increase. In 2021, there were 73,518 cases, which increased to 143,266 in 2022. In 2023, there were 114,720 cases, resulting in 894 deaths[4]. Bandung City is one of the regions in Indonesia that contributes the highest incidence of dengue. In 2021, the incidence of dengue in Bandung City was recorded at 3,743 cases, increasing to 5,205 cases in 2022 and resulting in 10 deaths[5].

The early identification of dengue outbreaks has the potential to enhance vector control efforts and permit public health authorities to implement proactive measures to prevent the spread of the disease [1]. A multitude of mathematical models have been employed to predict dengue incidence. Time series models are the most prevalent, as evidenced by studies conducted in Thailand [2], Singapore [3], Brazil [4] and China [5]. This model employs a combined approach between environmental and biological factors in order to forecast the risk of transmission and the magnitude of potential outbreaks. Furthermore, this model can integrate the complex interactions between environmental and biological factors that affect dengue transmission [6]. The models presented in some of these studies indicate that time series analysis is an invaluable tool for enhancing our understanding of dengue transmission dynamics and for the design of effective preventive measures to control the disease.

Time series analysis is a valuable tool in public

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[2] Centers for Disease Control and Prevention. Why is Dengue a Global Issue. URL: https://www.cdc.gov/dengue/training/cme/ccm/page51440.html

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[4] Ministry of Health of the Republic of Indonesia. Latest information on dengue up to week 8 2024. URL: https://p2pm.kemkes.go.id/publikasi/infografis/informasi-terkini-dbd-hingga-minggu-ke-8-2024

[5] Health Office of Bandung City. Health Profile of Bandung City in 2022. URL: https://dinkes.bandung.go.id/download/profil-kesehatan-2022

health and infectious disease surveillance [7]. Autoregressive Integrated Moving Average (ARIMA) model is a time series modelling technique that has been widely used to predict and forecast data with seasonal patterns. The model has proven effective in modelling and forecasting dengue incidence, revealing temporal patterns, and predicting future trends. The ARIMA model is versatile and has many practical applications in dengue prevention and control. The model is capable of identifying temporal patterns, thereby guiding targeted vector control measures during high-risk periods. Furthermore, the ARIMA model assists in developing an early warning system for dengue outbreaks, thereby improving the efficiency and effectiveness of vector control campaigns. These analyses provide insights into dengue transmission patterns and the impact of environmental and social factors on disease incidence [6]. The application of ARIMA modelling has facilitated a deeper understanding of temporal patterns, thereby enabling more effective prevention and control of outbreaks. This approach has been successfully employed in Brazil, Mexico, Singapore, Sri Lanka and Thailand [8].

The incidence of dengue cases in Indonesia is rising year on year, yet the efforts made to combat the disease are not yet optimal. Furthermore, the current treatment approach has not been proven effective in overcoming dengue, with the focus being on mitigating complications and reducing the severity of symptoms instead [9]. Consequently, there is a pressing necessity to implement effective prevention strategies. The ARIMA model is frequently employed in case forecasting research and provides insight into dengue epidemiology. However, in this study, the author sought to offer novel insights specific to the distinctive dynamics of dengue transmission in Bandung City. These insights can assist policymakers in developing early vigilance efforts and implementing dengue epidemiological surveillance, particularly with regard to place and time. The objective of this study is to forecast the incidence of dengue in order to facilitate more efficient dengue prevention and control efforts.

Materials and methods

Study design

This retrospective observational study was conducted using historical data of dengue cases in Bandung City, Indonesia from 2014 to 2023.

Study area

The study area of this research is Bandung City which is the capital of West Java Province, Indonesia, and is the third largest city in Indonesia. located at 107º36‘East, 6º55’ LS, and covers an area of 167.3/km². In 2023 the population of Bandung City is 2,569,107 people with a population density of approximately 15,000 people per square kilometre. Bandung City was chosen as the research location because it is a dengue endemic area and recorded a significantly higher amount of dengue cases from 2014 to 2023 compared to other regions.

Data collection

This study used secondary data from the Bandung City Health Office. The Disease Prevention and Control Unit of Bandung City Health Office provided monthly data on dengue incidence in Bandung City from January 2014 to December 2023. The monthly dataset contains a total of 120 monthly observations. The author used dengue cases covering 2014–2023 due to the availability of the dataset recorded from Bandung City Health Office. Dengue incidence data is something that must be reported in Bandung City routinely. The data available at the Bandung City Health Office are transferred data from community health center, hospitals and clinics, so this data is sufficient to describe the actual incidence.

Data management and statistical analysis

The forecasting data analysis method used R Studio software. The temporal pattern of dengue incidence in Bandung City was analysed using Autoregressive Integrated Moving Average (ARIMA), a statistical modelling approach that has been widely used for time series analysis. This approach was popularised by Box and Jenkins. During the study period, monthly dengue incidence cases were used to create an ARIMA time series analysis. In general, when dealing with data that does not show seasonal patterns, the model used is ARIMA (p, d, q). The parameters of the ARIMA model are as follows: p is the autoregressive (AR) number, which determines how many time periods are used to predict the current period. This parameter is determined from the partial autocorrelation function (PACF) diagram, d: the number of differentials taken for the static average and the parameter q represents the moving average (MA) number, which takes into account the deviation of the data series from the average of the series over a number of time periods to predict the current time period. These parameters are determined from the autocorrelation function (ACF) diagram. The evaluation of time series models includes the use of Akaike Information Criteria (AIC). Lower normalised AIC values are considered to be more favourable. Once the optimal model had been identified, the author proceeded to perform forecasting for 2024.

Ethical clearance

Ethical clearance and permission for this study was obtained from the Health Research Ethics Committee of Bhakti Kencana University with No. 079/09.KEPK/UBK/VII/2023.

Results

Figure 1 shows the map of Bandung City Area along with dengue incidence maps from 2014 to 2023.

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These maps highlight the dengue incidence based on 30 sub-districts. The highest cases occurred in 2022 at 5,205 cases. The highest number of cases is in Bojongloa Kidul Sub-district (299 cases), and the lowest number of cases is in Bandung Wetan Sub-district (65 cases). Meanwhile, the lowest number of cases occurred in 2017 at 1,786 cases. The highest number of cases was in Buah batu sub-district (134 cases) and the lowest number was in Cicadap sub-district (12 cases).

This study uses a dataset consisting of monthly dengue events in Bandung City from January 2014 to December 2023, which shows a random or non-seasonal pattern. The observed monthly dengue case series showed a stationary pattern as shown in **Figure 2**, *a*. To assess the stationarity of the data, the Dickey-Fuller test was performed and showed the data was stationary ($p = 0.01$). In the ACF plot, the value drops exponentially as it approaches 0 in Fig. 2, *b*. While the PACF that exceeds the maximum limit is at Lag 0, 1 and 3, then the appropriate model is AR = 3 seen in Fig. 2, *c*.

After identifying the model, we estimated the ARIMA model to determine the significant model. **Table 1** shows that the ARIMA models with significant coefficient estimates are ARIMA (3,0,1), ARIMA (3,0,2) and ARIMA (3,0,3).

The ARIMA models with significant coefficient estimates are ARIMA (3,0,1), ARIMA (3,0,2), and ARIMA (3,0,3). Diagnostic checking is done to ensure the best ARIMA model. The ACF plot of residuals does not exceed the boundary line for lag > 0, and the Ljung-box test shows that all values are above the boundary line, so the ARIMA (3,0,1) model is appropriate, otherwise there is no autocorrelation (**Fig. 3**, *a*). ACF plot of residuals exceeds the boundary line for lags > 0. The Ljung-box test shows that all values are above the boundary line, so the ARIMA (3,0,2) model is appropriate, otherwise there is no autocorrelation (Fig. 3, *b*). ACF plot of residuals exceeding the boundary line for lags > 0. The Ljung-box test shows that all values are above the boundary line, so the ARIMA (3,0,3) model is appropriate, otherwisethere is no autocorrelation (Fig. 3, *c*).

The ARIMA (3,0,1), ARIMA (3,0,2) and ARIMA (3,0,3) models are all good, so to determine the best ARIMA model, the Mean Absolute Percentage Error (MAPE), and Akaike information criterion (AIC) values are used. **Table 2** shows the values of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), and Akaike information criterion (AIC). The most suitable model

Table 1. Estimation of ARIMA Model

Model	AR *p*-value	MA *p*-value
ARIMA (0,0,1)	–	Significant
ARIMA (0,0,2)	–	Significant
ARIMA (0,0,3)	–	Significant
ARIMA (1,0,0)	Significant	–
ARIMA (1,0,1)	Significant	Not significant
ARIMA (1,0,2)	Significant	Not significant
ARIMA (1,0,3)	Significant	Not significant
ARIMA (2,0,0)	Significant	–
ARIMA (2,0,1)	Significant	Not significant
ARIMA (2,0,2)	Not significant	Not significant
ARIMA (3,0,0)	Significant	Not significant
ARIMA (3,0,1)	Significant	Significant
ARIMA (3,0,2)	Significant	Significant
ARIMA (3,0,3)	Significant	Significant

forecast result is the ARIMA (3,0,3) model, which can be seen from the MAPE value of 33.3437 and the AIC value of 0.1489.

ARIMA model (3,0,3) to forecast dengue incidence from January 2024 to December 2024, with a MAPE value of 33.3437 or 3.33%. The observed and forecasted values of dengue incidence for 2024 are presented in **Fig. 4**. The trend of dengue cases in Bandung City from January to December 2024 tends to increase.

The results of the forecast of dengue incidence in Bandung City in 2024 (**Table 3**), we found that the highest number of cases occurred in September 2024 which was 320 and the lowest in January 2024 which was 217 cases This finding is quite similar to the pattern of dengue incidence in observational data, so this model is sufficient to describe the forecast of dengue incidence in 2024.

Discussion

The incidence of dengue in Bandung City has consistently posed a significant public health concern in recent years. The city's dengue incidence rate is notably higher than that of other cities and districts, with a high mortality rate. Dengue incidence is typically highest during the rainy season [10], with population density also playing a role [11]. The Indonesian government has implemented dengue prevention and control efforts, including the eradication of mosquito nests [12].

Table 2. Mean Absolute Percentage Error (MAPE), and Akaike information criterion (AIC) on ARIMA Model

Model	RSME	MAE	MAPE	AIC
ARIMA (3,0,1)	114.0923	75.344	34.08223	0,1492
ARIMA (3,0,2)	111.3093	74.16202	33.87018	0,1490
ARIMA (3,0,3)	110.0493	73.42905	33.3437	0,1489

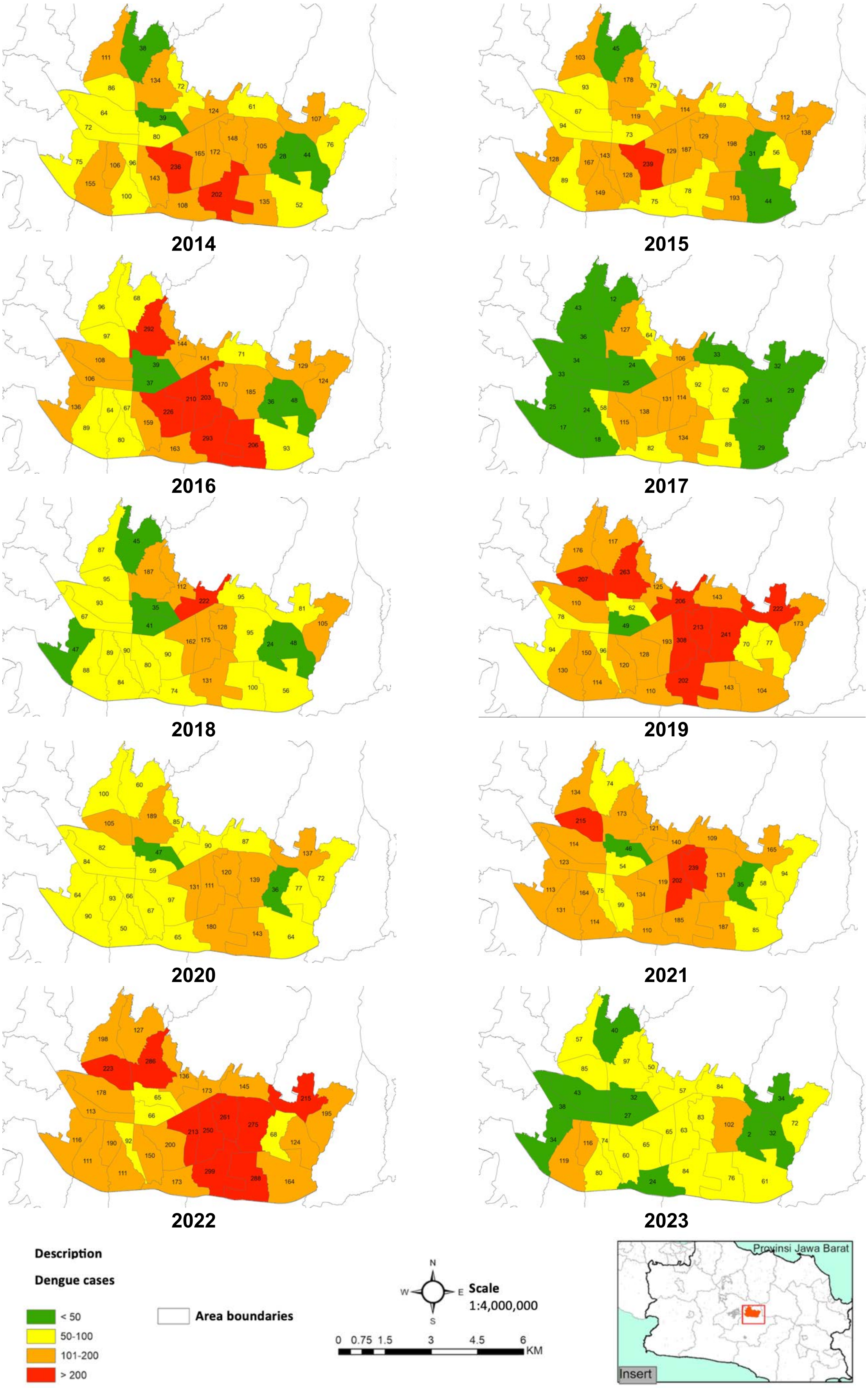

Fig. 1. Dengue incidence in Bandung City in 2014–2023.

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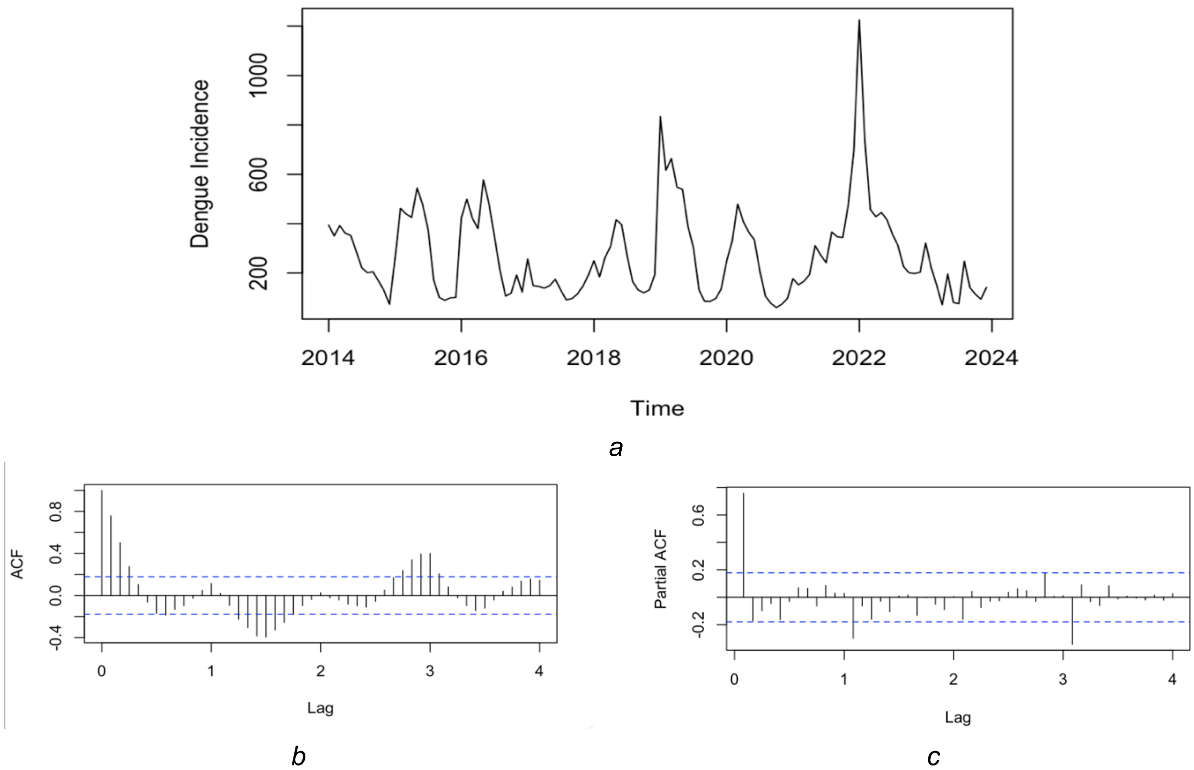

Fig. 2. Dengue incidence based on January 2014 to December 2023 in Bandung City (*a*), autocorrelation function (*b*), partial autocorrelation function (*c*).

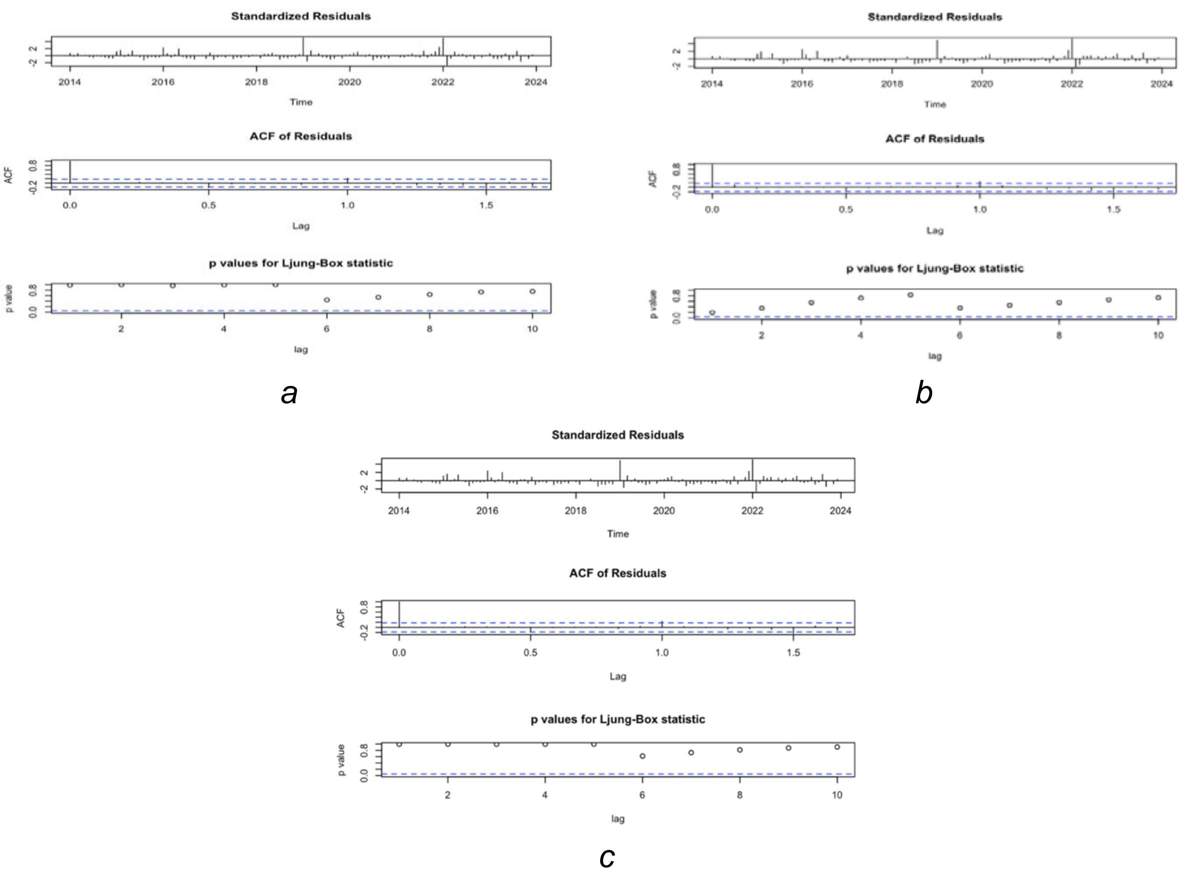

Fig. 3. Diagnostic checking of ARIMA Model (3,0,1) (*a*), ARIMA Model (3,0,2) (*b*), RIMA Model (3,0,3) (*c*).

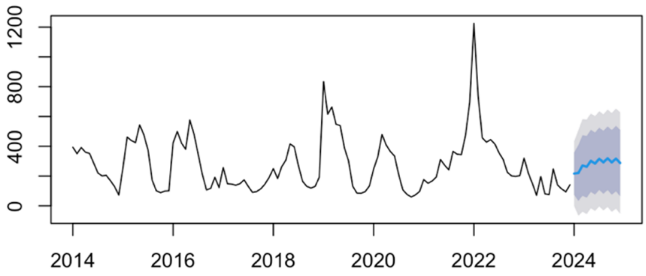

Fig. 4. Observed and predicted dengue incidence from ARIMA model (3,0,3) in 2024 in Bandung City.

Table 3. Prediction of dengue fever cases in Bandung City in 2024 obtained from the ARIMA model (3,0,3)

Month	Cases
Jan-24	217
Feb-24	221
Mar-24	272
Apr-24	263
May-24	303
Jun-24	285
Jul-24	316
Aug-24	293
Sep-24	320
Oct-24	293
Nov-24	318
Dec-24	289

Case experience, such as the ARIMA technique, plays an important role in the conduct of dengue prevention and control planning. This study employed the ARIMA technique to forecast dengue incidence in Bandung City. The findings of this study can serve as a source of information for the government and researchers in preparing and responding to dengue outbreaks in Indonesia.

This study utilises monthly dengue incidence data from January 2014 to December 2023. The SARIMA model was employed to forecast the number of dengue events in 2024. The accuracy of the SARIMA model is contingent upon the quality and availability of data, as well as the selection of appropriate model parameters and assumptions. In this study, the observation data is stationary. This study demonstrates that large data sets facilitate the generation of more accurate models and forecasts. The best model for forecasting Bandung City cases is the ARIMA model (3,0,3), which provides the most accurate forecast of dengue incidence. ARIMA models have been widely used in Southeast Asia, especially in Malaysia, Vietnam, Myanmar and Thailand. Some of these countries have used the ARIMA model to forecast dengue incidence effectively [13–16]. Another study in Indonesia posited that the ARIMA model can assist in the prediction of dengue cases and can be utilized by the government to design effective public health measures to prevent and control dengue incidence, particularly at the outset of an outbreak [17]. A study conducted Indonesia found that the SARIMA model accurately predicts monthly dengue cases, thereby supporting the development of an early warning system for dengue outbreaks [18].

The findings in Sri Lanka indicate that the ARIMA model has demonstrated its capacity in effectively forecasting weekly dengue cases. This makes it a viable proposition for forecasting weekly dengue incidence in the short term. The model can be utilised to improve the Ministry of Health's preparedness and response strategies, ultimately contributing to the proactive management of dengue outbreaks [19]. In Bandung City and Indonesia, the dengue incidence forecasting model can help in improving the existing strategies in preventing and controlling dengue disease. Furthermore, the prediction of cases can facilitate the response to outbreaks that do occur, given that Bandung City is an endemic area and that frequent outbreaks are a regular occurrence. Therefore, forecasting models are required.

The findings of this study have significant implications for dengue prevention policies and practices in Bandung City. The use of the ARIMA (3,0,3) forecasting model can provide important information about the appropriate strategies in preventing and controlling dengue incidence, including mosquito nest eradication measures and vector control. It is predicted that dengue incidence will increase in September 2024, which coincides with the beginning of the rainy season. This finding is consistent with research in Nepal which states a seasonal pattern of dengue incidence, with the development of cases in September, reaching the highest point in September-October. Dengue cases peak in months with the highest temperature and rainfall [20]. The spatial map of dengue incidence in Bandung City from 2014 to 2023 is quite varied, with several sub-districts exhibiting a high number of cases each year. Sub-districts with a high number of cases are areas with a high population density. Findings in Sri Lanka and Brazil have indicated that the spread of dengue vectors is due to demographic factors such as population density [21, 22]. Other studies have identified higher dengue incidence rates in certain areas due to climatic variations, socioeconomic status, urbanisation, and vector control efforts [23, 24].

The predictive accuracy of this model can be enhanced by incorporating the potential impact of climatic variables, such as temperature, humidity, precipitation and wind speed, on dengue transmission [25, 26]. These climatic factors are known to play a significant role in dengue transmission [27], and therefore, it is essential to include them in future research to enhance the predictive capacity of the model and facilitate a deeper understanding of disease mechanisms and the development of effective public health interventions. Bandung City is situated at an average altitude of 700 metres above sea level, which is conducive to the proliferation of Aedes aegypti mosquitoes. Research conducted in Colombia indicates that the Aedes aegypti mosquito is more prevalent at altitudes below 1,000 metres [28]. Furthermore, the seasonal increase in dengue incidence in Bandung City is attributed to the density of mosquito larvae. Previous findings have indicated that the entomological index, which is defined as the density of mosquito larvae, plays a significant role in the increase of dengue incidence in Bandung City [29].

Given the limitations of this study, including the potential influence of climatic factors, population density, altitude and high population mobility, it is crucial to develop a model to describe dengue case patterns in future studies. Overall, this study has significant implications for the public health of Bandung City and Indonesia. It is imperative to implement prevention efforts at the beginning of the peak cases to avoid the occurrence of dengue outbreaks.

Conclusion

This study presents a ARIMA model for forecasting dengue incidence in Bandung City, Indonesia. Monthly confirmed dengue events in Bandung City were obtained from 2014 to 2023 for this study, with the objective of forecasting dengue disease outbreaks in the early phase and enabling rapid response. The ARIMA model (3,0,3) proved to be the most accurate in forecasting future dengue incidence. The model predicts the peak of dengue cases in September 2024 with an estimated 320 cases. This model will be useful for dengue epidemiological surveillance and for policy makers in improving dengue prevention and control efforts. The spatial map shows that certain sub-districts had very high dengue incidence from 2014 to 2023, which emphasises the necessity for targeted intervention in high-risk areas for vector control. The incorporation of climatic variables, in conjunction with other factors such as population density, altitude and population mobility, is essential for the generation of more precise disease incidence forecasts. Consequently, these variables should be incorporated into the development of models designed to describe future dengue incidence patterns.

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