



Forecast of Dengue Hemorrhagic Fever Cases Based on Climate and Population Density Data Using Autoregressive Integrated Moving Average

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ARTICLE INFO

Article Type:
Research

Article History:
Received: 18 February 2026
Accepted: 30 March 2026
Published: 31 March 2026

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ORIGINAL ARTICLE

ABSTRACT

Dengue fever remains a major public health problem in Bali, with Denpasar consistently reporting high incidence rates in recent years. However, limited studies have quantitatively examined the influence of climate variability on dengue fever incidence and its temporal trends in this area. This study aimed to predict the trend of dengue fever incidence and to assess the impact of climate factors on dengue occurrence in Denpasar. This observational study used secondary data and was analyzed using cross-correlation, Pearson correlation, and Autoregressive Integrated Moving Average (ARIMA) time series modeling. The results of cross-correlation analysis showed that temperature had a significant negative correlation with dengue incidence, while rainfall showed a significant positive correlation. Humidity was not significantly associated with dengue incidence. The ARIMA model demonstrated good predictive performance with an R-squared value of 0.698, indicating that approximately 69.8% of the variation in dengue incidence could be explained by the model. The model also identified a consistent increase in dengue cases at the beginning of the year. These findings indicate that climate factors, particularly temperature and rainfall, play a significant role in influencing dengue incidence in Denpasar. The ARIMA model provides a reliable tool for early prediction of dengue outbreaks. Therefore, vector control and preventive interventions should be intensified at least one month prior to the expected increase in cases, particularly during periods of high rainfall.

Keywords: Dengue Fever, Forecasting, Temperature, Humidity, Rainfall.

ABSTRAK

Demam berdarah dengue tetap menjadi masalah kesehatan masyarakat yang signifikan di Bali, dengan Kota Denpasar yang secara konsisten melaporkan tingginya angka insidensi dalam beberapa tahun terakhir. Namun, hanya sedikit penelitian yang secara kuantitatif menelaah pengaruh variabilitas iklim terhadap insidensi demam berdarah dengue dan tren temporalnya di wilayah ini. Penelitian ini bertujuan untuk memprediksi tren kejadian demam berdarah dengue serta menilai dampak faktor iklim terhadap terjadinya demam berdarah dengue di Denpasar. Penelitian observasional ini menggunakan data sekunder dan dianalisis menggunakan uji cross-correlation, korelasi Pearson, serta pemodelan deret waktu Autoregressive Integrated Moving Average (ARIMA). Hasil analisis cross-correlation menunjukkan bahwa suhu memiliki korelasi negatif yang signifikan dengan insidensi demam berdarah dengue, sedangkan curah hujan menunjukkan korelasi positif yang signifikan. Kelembaban tidak berkorelasi secara signifikan dengan insidensi demam berdarah dengue. Model ARIMA menunjukkan kinerja prediksi yang baik dengan nilai R-squared sebesar 0,698, yang mengindikasikan bahwa sekitar 69,8% variasi insidensi demam berdarah dengue dapat dijelaskan oleh model tersebut. Model ini juga mengidentifikasi peningkatan kasus dengue yang konsisten pada awal tahun. Temuan ini menunjukkan bahwa faktor iklim, khususnya suhu dan curah hujan, berperan penting dalam memengaruhi insidensi dengue di Denpasar. Model ARIMA memberikan alat prediksi dini yang andal untuk kewaspadaan terhadap potensi wabah dengue. Oleh karena itu, pengendalian vektor dan intervensi pencegahan perlu ditingkatkan setidaknya satu bulan sebelum peningkatan kasus yang diperkirakan terjadi, terutama pada periode dengan curah hujan tinggi.

Kata Kunci: Demam Berdarah Dengue, Peramalan, Suhu, Kelembapan, Curah Hujan.

INTRODUCTION

Dengue hemorrhagic fever (DHF) is a disease caused by dengue virus (Parveen et al., 2023) and transmitted by *Aedes* mosquitoes. The incidence of dengue has increased worldwide for decades, especially in tropical countries (Siregar, Makmur, & Saprin, 2018). Previous studies showed that 390 million people per year are infected with dengue virus and more than 128 countries are at risk (WHO, 2019). Currently, two-thirds of the world population is at risk of being infected with dengue virus. Therefore, DHF remains a global health problem resulting in a high disease burden (Nadjib et al., 2019).

Indonesia is one of the countries significantly threatened by dengue virus transmission (Haryanto, 2018; Yudhastuti & Lusno, 2021). Since the first reported outbreak in Surabaya and Jakarta in 1968, DHF has spread to all provinces and has become endemic nationwide (Hasmiwati et al., 2018; Sari, Adelwin, & Rinawan, 2020; Megawati et al., 2017). Over the past 45 years, the incidence of DHF has increased rapidly, accompanied by changes in the mean age of cases and annual incidence rates. In recent years, Bali and Kalimantan have reported some of the highest dengue incidence rates in Indonesia (Harapan et al., 2019; Maulana et al., 2022), indicating persistent transmission and highlighting the need for more targeted local interventions.

Bali is recognized as a dengue hotspot, where all four dengue virus serotypes have been identified (Megawati et al., 2017). The burden of DHF in Bali is particularly high in Denpasar (Dhewantara et al., 2019). As a major international tourism destination, Denpasar experiences high population mobility, including international and domestic travelers, which contributes to sustained dengue transmission (Masyeni et al., 2018; Dhewantara et al., 2019). This continuous influx of visitors from both endemic and non-endemic regions increases the complexity of dengue dynamics and reinforces the urgency of effective surveillance and early warning systems at the local level.

Environmental and climatic factors play a critical role in dengue transmission dynamics. Climate patterns such as temperature, humidity, and rainfall have been shown to influence mosquito breeding, survival, and virus transmission (Arsin et al., 2020; Prasad et al., 2024). Previous studies indicated that higher temperatures may reduce DHF cases, whereas increased humidity and rainfall tend to elevate transmission risk (Widyorini et al., 2017). These factors are particularly relevant in tropical regions like Denpasar, where seasonal variations, especially during the rainy season, can trigger spikes in dengue incidence. Therefore, monitoring climate variables is essential to support the development of an effective early warning system.

Various prevention efforts have been implemented by the Denpasar City Government, including vector control measures such as fogging, community-based interventions like the 3M Plus program, and health education initiatives aimed at improving environmental sanitation (Bali Provincial Health Office, 2020). However, despite these efforts, dengue incidence remains high, indicating the need for more predictive and data-driven approaches to complement existing control strategies.

Although numerous studies have examined the relationship between climate factors and dengue incidence, and others have applied time series models for forecasting, there is still a lack of studies that integrate time series forecasting with climate variables in the specific context of Denpasar. Moreover, the dynamic nature of dengue transmission in a high-mobility tourism city has not been adequately captured in previous research. This represents a critical research gap, as localized predictive models are essential for timely and effective intervention.

The Autoregressive Integrated Moving Average (ARIMA) model is widely used in time series analysis due to its ability to capture temporal patterns, trends, and seasonality in epidemiological data. ARIMA is particularly suitable for forecasting short-term disease incidence and can provide valuable insights for public health decision-making and early warning systems. By applying ARIMA in this study, it is expected to generate accurate predictions of DHF cases and support proactive prevention strategies.

Based on this background, forecasting DHF cases in Denpasar using ARIMA is needed to provide useful information for the government and community to strengthen prevention efforts. Therefore, the objective of this study was to analyze and predict DHF trends and to

examine the relationship between climate factors (temperature, humidity, and rainfall) and dengue incidence in Denpasar.

RESEARCH METHODS

This study employed a quantitative retrospective time series design to analyze and forecast DHF incidence in Denpasar City, Bali, Indonesia, from January 2015 to December 2019, on a monthly basis. The variables in this study were operationally defined as follows. DHF incidence referred to the number of reported dengue hemorrhagic fever cases per month in Denpasar. Temperature was defined as the average monthly air temperature measured in degrees Celsius, humidity as the average monthly relative humidity expressed as a percentage, and rainfall as the total monthly precipitation measured in millimeters. Population density referred to the number of people per square kilometer in Denpasar.

This study utilized secondary data obtained from official institutions. Monthly DHF incidence data from 2015 to 2019 were collected from the Denpasar City Health Office. Climate data, including temperature ($^{\circ}\text{C}$), humidity (%), and rainfall (mm), were obtained from the Meteorology, Climatology, and Geophysical Agency, Denpasar for the same period. In addition, population density data (people per km^2) were obtained from the Denpasar Statistics Bureau for the year 2019. Data analysis was conducted using SPSS software with a time series approach. Descriptive analysis was first performed using tabulations and graphical presentations to illustrate trends in DHF incidence, climate variables, and population density. The DHF time series data were initially found to be non-stationary; therefore, natural logarithm transformation and differencing were applied to achieve stationarity prior to model development.

The ARIMA modeling procedure was carried out systematically, beginning with model identification using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to determine potential model structures. Several candidate models, including ARIMA (1,0,1), ARIMA (2,0,1), and ARIMA (3,0,1), were then estimated. Parameter significance was evaluated using t-tests, followed by diagnostic checking to assess model adequacy. Model selection was based on multiple evaluation criteria, including R-squared (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Maximum Absolute Error (MaxAE). The best model was determined by the highest R^2 value and the lowest error values. The selected ARIMA model was subsequently used to forecast DHF incidence for the following periods (2020–2021). To examine the relationship between climate factors and DHF incidence, cross-correlation analysis was conducted across multiple time lags to identify potential delayed effects of temperature, humidity, and rainfall on DHF cases.

This study used secondary data derived from routine program reports of the Denpasar City Health Office and other government agencies; therefore, it did not involve direct human subjects and did not require formal ethical approval. Nevertheless, this study adhered to ethical principles of health research, including maintaining data confidentiality, ensuring data security, and using the data solely for research purposes.

RESULTS

The time series analysis of DHF incidence in Denpasar City was conducted using the ARIMA model. The original data were non-stationary; therefore, natural logarithm transformation and differencing were applied prior to model estimation. The resulting model structure is presented in Figure 1.

Three candidate models ARIMA (1,0,1), ARIMA (2,0,1), and ARIMA (3,0,1)—were evaluated (Table 1). In the ARIMA (2,0,1) model, the constant and autoregressive terms at lag 1 and lag 2 were statistically significant ($p < 0.05$), indicating that current DHF incidence is significantly influenced by incidence in the previous two months. In contrast, the moving average component was not statistically significant.

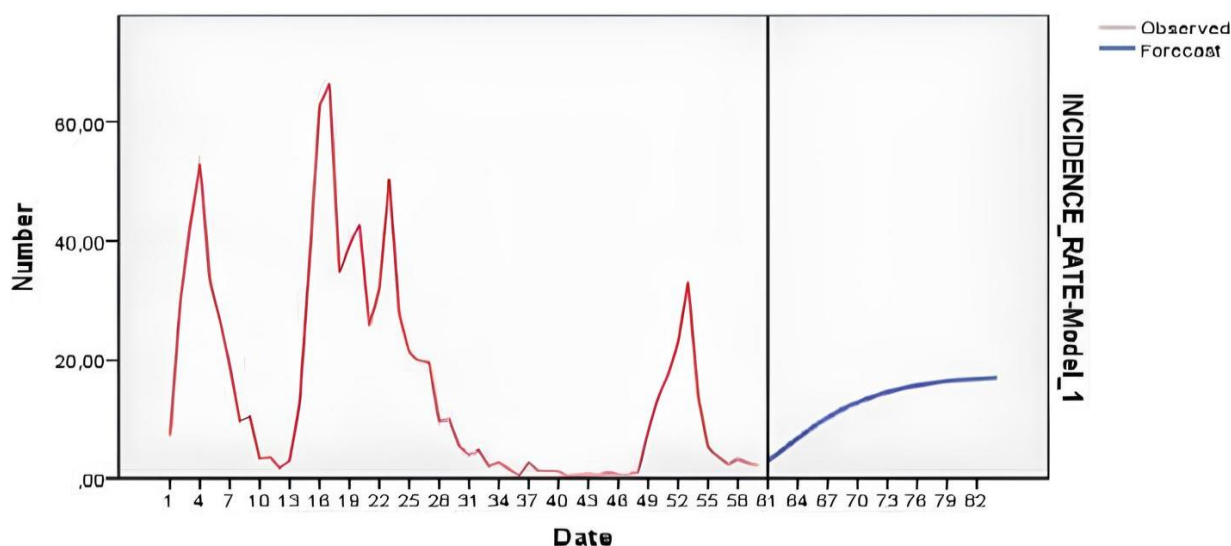


Figure 1. Prediction of DHF Distribution in Denpasar.

Table 1. The Analysis Results of the ARIMA in First Stage.

		Coefficient	t	p-value
ARIMA (1,0,1)	Constant	1.775	2.714	0.009
	AR Lag 1	0.866	11.855	0.000
	MA Lag 1	-0.069	-0.457	0.649
ARIMA (2,0,1)	Constant	1.757	3.466	0.001
	AR Lag 1	1.654	4.817	0.000
	Lag 2	-0.711	-2.425	0.019
	MA Lag 1	0.670	1.661	0.102
ARIMA (3,0,1)	Constant	1.759	3.466	0.001
	AR Lag 1	1.347	2.598	0.012
	Lag 2	-0.285	-0.499	0.620
	Lag 3	-0.160	-0.990	0.326
	MA Lag 1	0.425	0.815	0.419

Table 2. The Analysis Results of the ARIMA in Second Stage.

	R-squared	RMSE	MAPE	MaE	MaxAE
ARIMA (1,0,1)	0.693	9.663	84.926	6.306	27.904
ARIMA (2,0,1)	0.698	9.659	80.873	5.838	32.742
ARIMA (3,0,1)	0.672	10.154	80.349	6.112	37.152

Model comparison based on goodness-of-fit and error metrics (Table 2) showed that ARIMA (2,0,1) had the highest R^2 value (0.698) and relatively lower RMSE, MAPE, MAE, and MaxAE compared to the other models. This indicates that the model explains approximately 69.8% of the variability in DHF incidence and provides the best fit among the candidate models. The model also captured a clear seasonal pattern, with DHF incidence increasing consistently in the early months of the year, particularly between February and May, as illustrated in Figure 1.

The patterns of climate variables during 2015–2019 are presented in Figure 2. Temperature remained relatively stable across the study period with minor seasonal fluctuations. In contrast, rainfall exhibited pronounced variability with clear seasonal peaks, while humidity showed moderate variation without a distinct pattern aligned with DHF incidence. These patterns suggest that rainfall variability may play a more prominent role in influencing DHF dynamics compared to temperature and humidity.

The relationship between climate variables and DHF incidence was assessed using cross-correlation analysis (Table 3), with graphical representation shown in Figures 3–5.

Temperature demonstrated a negative correlation at lag -3 ($r = -0.339$), indicating that higher temperatures were associated with a decrease in DHF incidence approximately three months later (Figure 3). This lag was selected based on the highest correlation magnitude exceeding the standard error threshold, suggesting a meaningful delayed association.

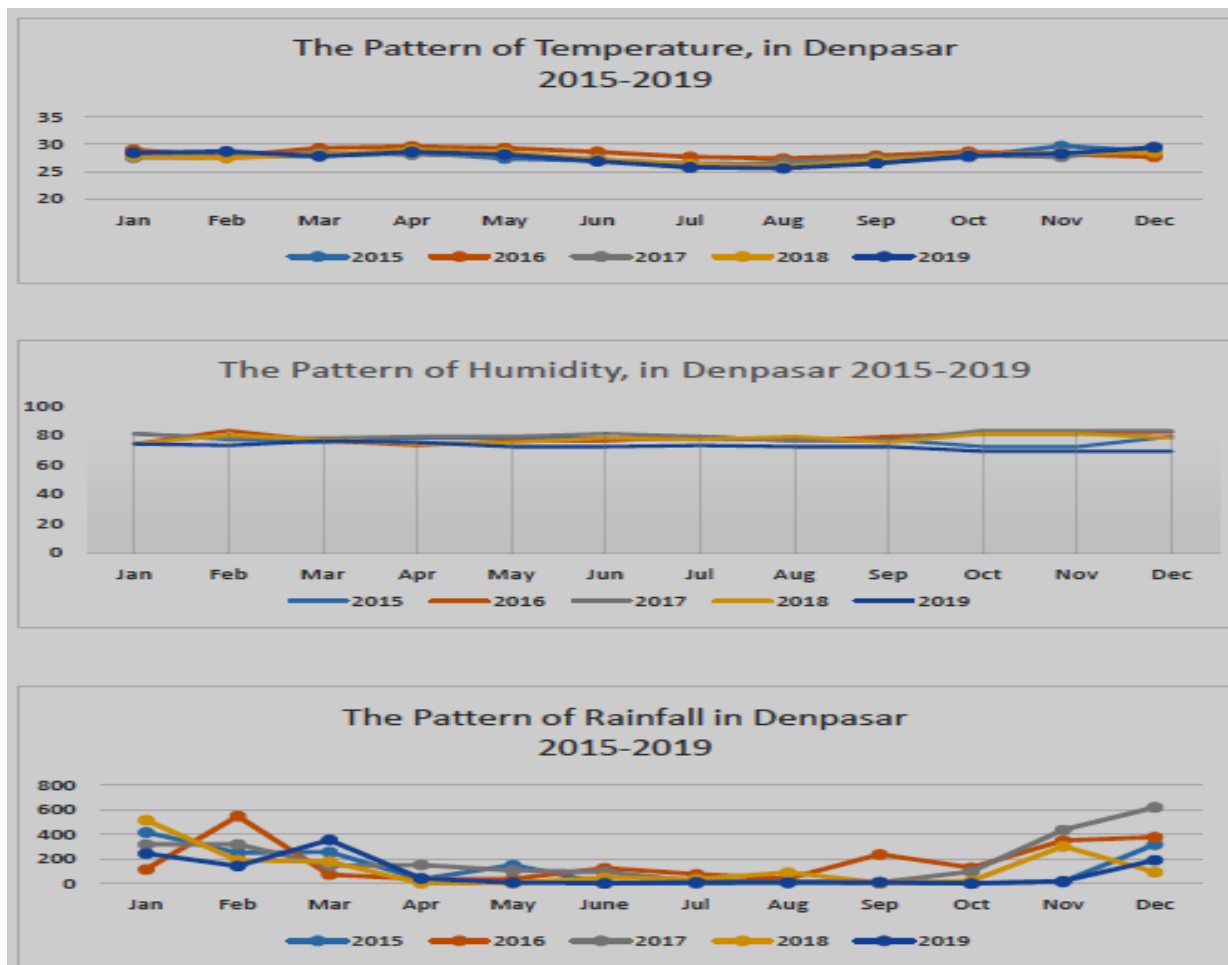


Figure 2. The Pattern of Climate Factors (Temperature, Humidity, and Rainfall) in Denpasar 2015-2019

Table 3. The Effect of Climate Factors on DHF

Lag	Temperature (°C)	Humidity (%)	Rainfall (mm)	Std Err.
	Cross-correlation	Cross-correlation	Cross-correlation	
-7	0.262	-0.003	0.044	0.139
-6	-0.033	-0.098	-0.086	0.137
-5	-0.137	0.081	-0.040	0.136
-4	-0.260	-0.041	-0.090	0.135
-3	-0.339	-0.004	-0.027	0.134
-2	-0.048	0.162	-0.098	0.132
-1	0.039	-0.065	0.027	0.131
0	0.248	-0.207	-0.221	0.130
1	0.146	-0.034	-0.059	0.131
2	-0.079	0.130	0.304	0.132
3	-0.037	0.099	0.160	0.134
4	0.186	-0.091	-0.014	0.135
5	0.186	0.097	0.042	0.136
6	0.083	-0.021	0.095	0.137
7	-0.72	-0.099	-0.201	0.139

Rainfall showed a positive correlation at lag 2 ($r = 0.304$), indicating that increased rainfall was followed by an increase in DHF incidence after approximately two months (Figure 5). This finding is consistent with the biological mechanism of mosquito breeding cycles and subsequent disease transmission.

In contrast, humidity did not show a meaningful correlation with DHF incidence across all observed lags, as the correlation coefficients did not exceed the standard error threshold (Table 3; Figure 4).

The interpretation of cross-correlation results was based on comparison with standard error values as an approximate indicator of statistical relevance. However, formal confidence intervals were not calculated, and this limitation should be considered when interpreting the strength of these associations.

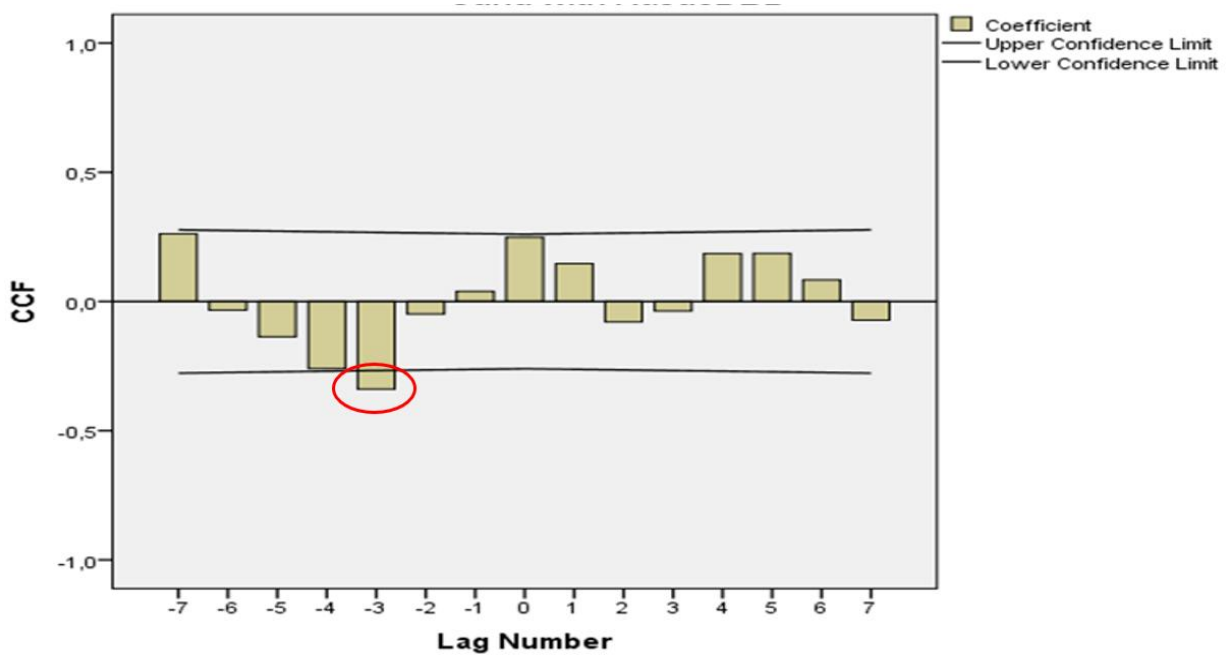


Figure 3. The effect of temperature on DHF

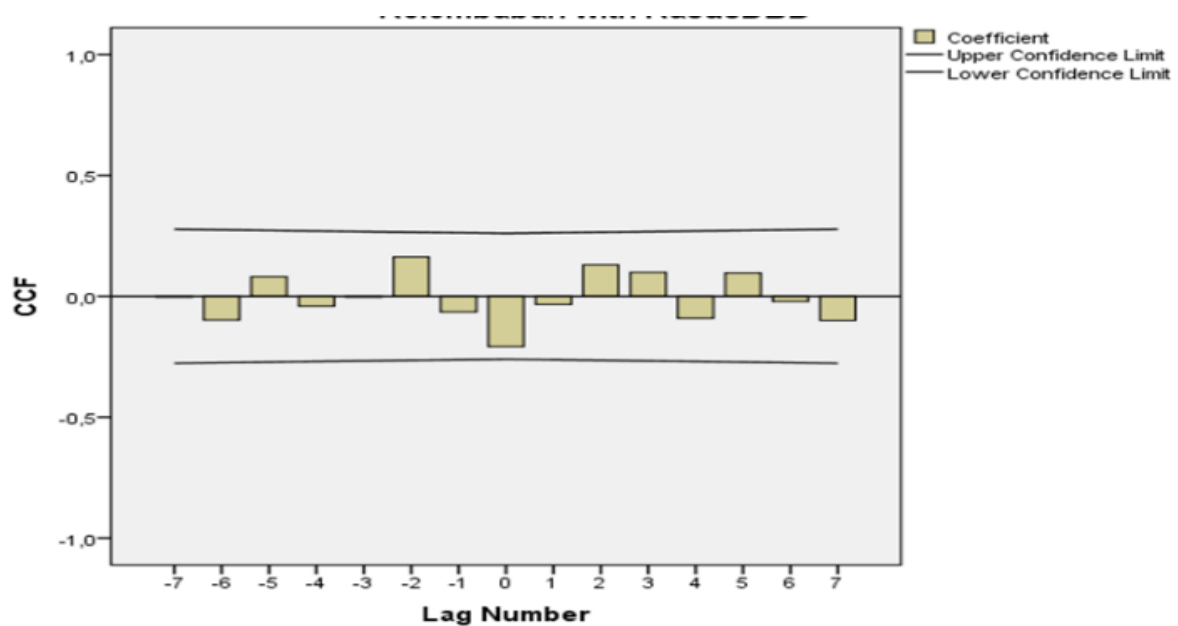


Figure 4. The effect of humidity on DHF

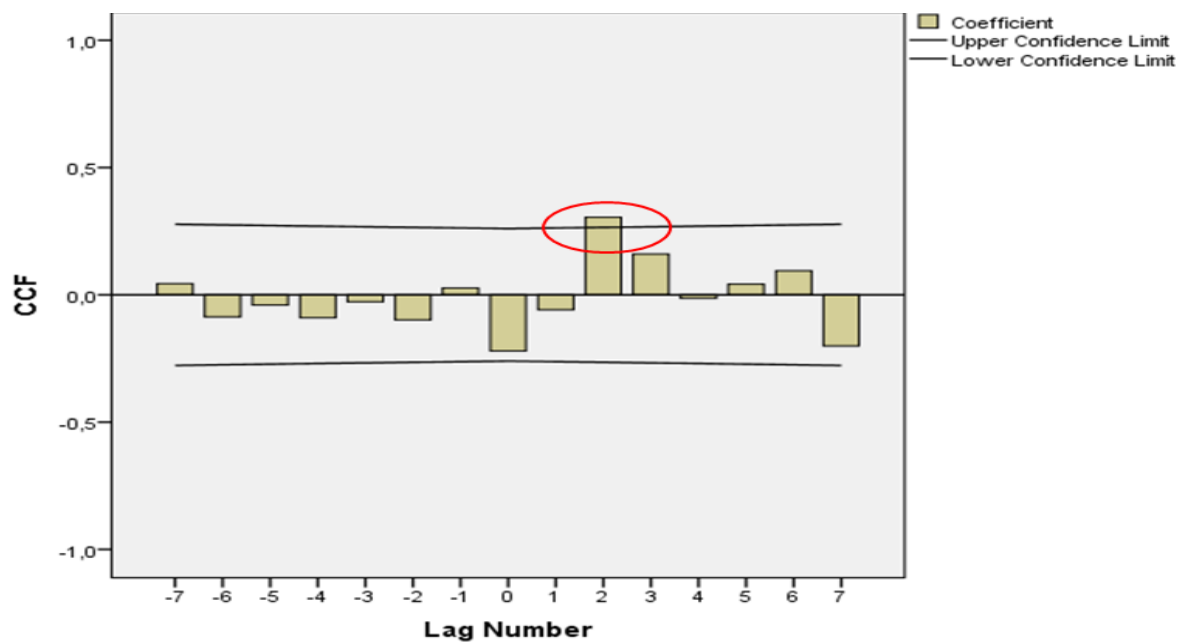


Figure 5. The effect of rainfall on DHF.

DISCUSSION

The findings of this study confirm that DHF incidence in Denpasar follows a clear seasonal pattern, with cases increasing in the early months of the year and peaking between February and May. This pattern is consistent with previous studies conducted in Bali and other regions in Indonesia, which reported peak dengue incidence occurring around April–May (Maulana et al., 2022; Yudhastuti et al., 2022; Dhewantara et al., 2019). Such seasonal trends are closely associated with climatic conditions, particularly the transition from the rainy to the early dry season, which creates favorable environments for mosquito breeding and subsequent disease transmission.

The ARIMA (2,0,1) model identified in this study indicates that DHF incidence is significantly influenced by cases in the previous one to two months, highlighting a short-term temporal dependency in transmission dynamics. Rather than merely describing trends, this finding suggests that dengue transmission in Denpasar is driven by recent transmission intensity, which may reflect ongoing local transmission cycles and delayed reporting or detection. The model’s ability to explain approximately 69.8% of the variability in DHF incidence further supports its utility for short-term forecasting, particularly for early warning systems.

The relationship between temperature and DHF incidence in this study showed a negative association at a three-month lag, which contrasts with much of the existing literature that typically reports a positive relationship between temperature and dengue transmission (Ramachandran et al., 2016). This apparent contradiction may be explained by several factors. First, temperature in Denpasar remains within a relatively narrow and optimal range (approximately 27–30 °C), which is already conducive to mosquito development (Blasius et al., 2019; Reinhold et al., 2018). Therefore, further increases in temperature may not enhance transmission but instead reduce mosquito survival or viral replication efficiency under certain conditions. Second, the delayed (lagged) negative effect suggests that temperature may influence earlier stages of the mosquito life cycle, leading to indirect and time-dependent impacts on disease incidence. These findings highlight the importance of considering non-linear and lagged effects of temperature in dengue transmission models.

In contrast, humidity was not found to be associated with DHF incidence in this study. Although previous studies have suggested that humidity plays a role in mosquito survival and larval indices (Brown et al., 2023; Heriyani, 2019; Sintorini, 2018), the lack of association observed here may be due to the relatively stable humidity levels in Denpasar throughout the year. This limited variability may reduce its explanatory power in time series analysis. Similar findings have also been reported in other studies, indicating that humidity may not always be a dominant driver of dengue incidence (Ishak & Kasman, 2018).

Rainfall, on the other hand, demonstrated a positive association with DHF incidence at a two-month lag, which is consistent with the biological mechanism of dengue transmission. Increased rainfall creates additional breeding sites for *Aedes* mosquitoes, followed by a time delay for mosquito development and virus transmission to humans (Yudhastuti & Lusno, 2021; Trisandy et al., 2021). This finding reinforces the role of rainfall as a key environmental driver of dengue transmission and supports its inclusion in early warning and prediction models.

Despite these findings, several limitations should be acknowledged. This study relied on secondary data from routine surveillance reports, which may be subject to reporting bias and data completeness issues. The relatively short observation period (2015–2019) may limit the ability to capture long-term trends and variability. In addition, the ARIMA model is based on historical patterns and may not fully account for unexpected changes such as outbreaks, intervention programs, or climate anomalies. The cross-correlation analysis identifies temporal associations but does not establish causal relationships, and formal confidence intervals were not estimated. Furthermore, other important determinants of DHF transmission, such as vector density, human mobility, and environmental factors, were not included in the analysis.

From a public health perspective, these findings have important implications. The identified seasonal pattern and lag effects suggest that preventive interventions should be intensified prior to the peak transmission period, particularly during the early rainy season. Vector control strategies, environmental management, and community-based interventions should be implemented at least one to two months before the expected increase in cases. In addition, the ARIMA model developed in this study could be integrated into local surveillance systems as an early warning tool to support timely decision-making. Future research should focus on incorporating additional variables and using higher-resolution data (e.g., weekly data) to improve predictive accuracy and better inform dengue control policies.

CONCLUSION

DHF incidence in Denpasar exhibits a clear seasonal pattern, increasing between February and May. The ARIMA (2,0,1) model was identified as the best-performing model ($R^2 = 0.698$), indicating that it explains approximately 69.8% of the variability in DHF incidence and is suitable for short-term forecasting. The model shows that current incidence is influenced by cases in the previous one to two months. Cross-correlation analysis revealed that temperature was negatively associated with DHF incidence at a lag of three months ($r = -0.339$), while rainfall showed a positive association at a lag of two months ($r = 0.304$), and humidity was not significantly associated. These findings emphasize the importance of incorporating temporal and climate factors into early warning systems, with interventions ideally implemented one to two months before peak transmission.

REFERENCES

- Arsin, A. A., Istiqamah, S. N. A., Elisafitri, R., Nurdin, M. A., Sirajuddin, S., Pulubuhu, D. A. T., ... & Yani, A. (2020). Correlational study of climate factor, mobility and the incidence of Dengue Hemorrhagic Fever in Kendari, Indonesia. *Enfermería Clínica*, 30, 280-284. <https://doi.org/10.1016/j.enfcli.2020.06.064>
- Bali Provincial Health Office. (2020). *Bali provincial health profile 2019*. Denpasar, Indonesia: Bali Provincial Health Office.
- Blasius, J., Alimi, A. Z.B, Mas'ud, M. A. B., & Dom, N. C. (2019). A scoping review of research on factors affecting the oviposition, development and survival of *Aedes* mosquitoes. *Asia Pacific Environmental and Occupational Health Journal*, 5(1), 27-39.
- Brown, J. J., Pascual, M., Wimberly, M. C., Johnson, L. R., & Murdock, C. C. (2023). Humidity—The overlooked variable in the thermal biology of mosquito-borne disease. *Ecology letters*, 26(7), 1029-1049. <https://doi.org/10.1111/ele.14228>
- Dhewantara, P. W., Marina, R., Puspita, T., Ariati, Y., Purwanto, E., Hananto, M., ... & Magalhaes, R. J. S. (2019). Spatial and temporal variation of dengue incidence in the island of Bali, Indonesia: An ecological study. *Travel medicine and infectious disease*, 32, 101437. <https://doi.org/10.1016/j.tmaid.2019.06.008>
- Harapan, H., Michie, A., Mudatsir, M., Sasmono, R. T., & Imrie, A. (2019). Epidemiology of dengue hemorrhagic fever in Indonesia: analysis of five decades data from the National

- Disease Surveillance. *BMC research notes*, 12(1), 350-358. <https://doi.org/10.1186/s13104-019-4379-9>
- Haryanto, B. (2018). Indonesia dengue fever: Status and challenges. *Current Topics in Tropical Emerging Diseases and Travel Medicine*, 1(1), 1–6. <https://doi.org/10.5772/intechopen.82290>
- Rusjdi, S. R., & Nofita, E. (2018). Detection of Ace-1 gene with insecticides resistance in *Aedes aegypti* populations from DHF-endemic areas in Padang, Indonesia. *Biodiversitas*, 19(1), 31-36. <https://doi.org/10.13057/biodiv/d190105>
- Heriyani, F. (2019). Correlation between air temperature and humidity with the presence of *Aedes aegypti* larvae. *Berkala Kedokteran*, 15(1), 1-6. <https://dx.doi.org/10.20527/jbk.v15i1.6086>
- Ishak, N. I., & Kasman, K. (2018). Climate factors and DHF incidence in Banjarmasin. *Public Health of Indonesia*, 4(3), 121–127.
- Maulana, M. R., Yudhastuti, R., Lusno, M. F. D., Mirasa, Y. A., Haksama, S., & Husnina, Z. (2023). Climate and visitors as the influencing factors of dengue fever in Badung District of Bali, Indonesia. *International Journal of Environmental Health Research*, 33(9), 924-935. <https://doi.org/10.1080/09603123.2022.2065249>
- Masyeni, S., Yohan, B., Somia, I. K. A., Myint, K. S. A., & Sasmono, R. T. (2018). Dengue infection in international travellers visiting Bali, Indonesia. *Journal of travel medicine*, 25(1), 61-67. <https://doi.org/10.1093/jtm/tay061>
- Megawati, D., Masyeni, S., Yohan, B., Lestari, A., Hayati, R. F., Meutiawati, F., Suryana, K., Widarsa, T., Budiya, D. G., Budiya, N., Myint, K. S. A., & Sasmono, R. T. (2017). Dengue in Bali: Clinical characteristics and genetic diversity of circulating dengue viruses. *PLoS neglected tropical diseases*, 11(5), e0005483. <https://doi.org/10.1371/journal.pntd.0005483>
- Nadjib, M., Setiawan, E., Putri, S., Nealon, J., Beucher, S., Hadinegoro, S. R., Permanasari, V. Y., Sari, K., Wahyono, T. Y. M., Kristin, E., Wirawan, D. N., & Thabrany, H. (2019). Economic burden of dengue in Indonesia. *PLoS neglected tropical diseases*, 13(1), e0007038. <https://doi.org/10.1371/journal.pntd.0007038>
- Parveen, S., Riaz, Z., Saeed, S., Ishaque, U., Sultana, M., Faiz, Z., Shafqat, Z., Shabbir, S., Ashraf, S., & Mariam, A. (2023). Dengue hemorrhagic fever: a growing global menace. *Journal of water and health*, 21(11), 1632–1650. <https://doi.org/10.2166/wh.2023.114>
- Prasad, P., Gupta, S. K., Mahto, K. K., Kumar, G., Rani, A., Velan, I., ... & Singh, H. (2024). Influence of climatic factors on the life stages of *Aedes* mosquitoes and vectorial transmission: A review. *Journal of Vector Borne Diseases*, 61(2), 158-166.
- Prasad, P., Gupta, S. K., Mahto, K. K., Kumar, G., Rani, A., Velan, I., Arya, D. K., & Singh, H. (2024). Influence of climatic factors on the life stages of *Aedes* mosquitoes and vectorial transmission: A review. *Journal of vector borne diseases*, 61(2), 158-166. https://doi.org/10.4103/JVBD.JVBD_42_24
- Ramachandran, V. G., Roy, P., Das, S., Mogha, N. S., & Bansal, A. K. (2016). Empirical model for estimating dengue incidence using temperature, rainfall, and relative humidity: a 19-year retrospective analysis in East Delhi. *Epidemiology and health*, 38, e2016052. <https://doi.org/10.4178/epih.e2016052>
- Reinhold, J. M., Lazzari, C. R., & Lahondère, C. (2018). Effects of the Environmental Temperature on *Aedes aegypti* and *Aedes albopictus* Mosquitoes: A Review. *Insects*, 9(4), 158. <https://doi.org/10.3390/insects9040158>
- Sari, S. Y. I., Adelwin, Y., & Rinawan, F. R. (2020). Land Use Changes and Cluster Identification of Dengue Hemorrhagic Fever Cases in Bandung, Indonesia. *Tropical medicine and infectious disease*, 5(2), 70. <https://doi.org/10.3390/tropicalmed5020070>
- Sintorini, M. M. (2018). Temperature and humidity with mosquito density. *IOP Conference Series: Earth and Environmental Science*, 106, 1-6. Retrieved from <https://iopscience.iop.org/article/10.1088/1755-1315/106/1/012033/pdf>
- Siregar, F. A., Makmur, T., & Saprin, S. (2018). Forecasting dengue hemorrhagic fever cases using ARIMA model: a case study in Asahan district. *IOP Conference Series: Materials Science and Engineering*, 300, 1-6. Retrieved from <https://iopscience.iop.org/article/10.1088/1757-899X/300/1/012032/pdf>

- Trisandy, A. Y., Maruf, M. A., Yudhastuti, R., Lusno, M. F. D., & Notobroto, H. B. (2021). Large-Scale Social Restriction (LSSR) Policy and Dengue Hemorrhagic Fever during the Covid-19 Pandemic in Indonesia: A Case Study of Five Subregions of East Java Province. *Jurnal Kesehatan Masyarakat*, 16(1), 49-52.
- Widyorini, P., Shafrin, K. A., Wahyuningsih, N. E., & Murwani, R. (2017). Dengue Hemorrhagic Fever (DHF) Cases in Semarang City are Related to Air Temperature, Humidity, and Rainfall. *Advanced Science Letters*, 23(4), 3283-3287. <https://doi.org/10.1166/asl.2017.9166>
- WHO. (2019). *Strong country capacity, improved tools and community engagement critical to enhancing dengue prevention and control*. Geneva: World Health Organization. Retrieved from <https://www.who.int/news/item/14-11-2019-strong-country-capacity-improved-tools-and-community-engagement-critical-to-enhancing-dengue-prevention-and-control>
- Yudhastuti, R., & Lusno, M. F. D. (2021). Climate factors for dengue control model in Bali. *Annals of Tropical Medicine and Public Health*, 24(1), 1–8.
- Yudhastuti, R., Lusno, M.F.D., Mirasa, Y.A., & Husnina, Z. (2022). Dengue dynamics in Bali 2010–2018. *Acta Medica Iranica*, 30(6), 366–373. <https://doi.org/10.18502/acta.v60i6.10042>