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RESEARCH **Open Access**

Early Detection of Dengue Fever Susceptibility using Climate Parameters and Larval Density

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Abstract
Dengue infection remains a vital public health challenge in Indonesia, especially in Pontianak City, marked by fluctuating case numbers and unpredictable transmission patterns influenced by climate and environmental factors. Current prevention efforts are often hampered by the lack of precise, integrated early warning information about regional vulnerability. This study aims to develop and evaluate a predictive model for dengue infection vulnerability by incorporating climate factors (rainfall intensity, humidity), population density, and larval-free index (LFI) to establish an accurate early warning system. An observational analytic study with a cross-sectional design was carried out using data from 2022 to 2024 in Pontianak. The study examined monthly rainfall intensity, relative humidity, population density, and LFI as predictors for dengue incidence. Data were analyzed using univariate, bivariate, and multivariate logistic regression analysis to assess regional vulnerability. The results show that rainfall intensity (p= 0.025; AOR= 2.097; 1.100 - 3.398) and LFI (p= 0.042; AOR= 1.102; 1.100 - 3.398) were the predictor of dengue risk. The prediction model can support stakeholders and the community in implementing timely and targeted prevention strategies to lessen the burden of dengue infection

Keywords: *Climate Factors; Dengue Infection; Early Warning System; Susceptibility Prediction; Pontianak.*

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1. INTRODUCTION

Dengue fever is the most widespread arboviral disease worldwide, with a rapidly increasing global burden driven by climate variability, urbanization, and population growth. In 2024, reported dengue cases exceeded 14 million across more than 90 countries, marking the highest incidence on record and underscoring dengue as an escalating global health and environmental challenge, particularly in tropical and subtropical regions (Anas et al., 2025). In 2024, more than 14 million dengue cases were reported worldwide, doubling the burden recorded in 2023, with active transmission documented in over 90 countries (Yang et al., 2025; Zhang et al., 2025). Southeast Asia remains one of the most affected regions, reflecting the strong influence of climate, environmental, and demographic conditions on dengue transmission dynamics (Nugraheni et al., 2026).

Indonesia remains among the countries with sustained dengue transmission. National surveillance recorded over 244,000 cases in 2024, with pronounced spatial and temporal variability at subnational levels (Mamenun et al., 2024). In West Kalimantan and Pontianak City, annual fluctuations in reported cases coexist with persistent transmission, indicating that relatively low incidence does not equate to low vulnerability and highlighting the need for proactive, location-specific risk assessment (Dinkes Kalbar, 2024).

Dengue transmission is strongly shaped by meteorological and environmental conditions that regulate Aedes aegypti dynamics (Nosrat et al., 2021). Temperature (Aulia, 2020), rainfall (Abdullah et al., 2022), and humidity directly influences mosquito survival (Caldwell et al., 2021), breeding, and viral replication, while demographic factors such as population density and larva-free rates modulate human–vector contact (Lahondère et al., 2023). Previous studies have demonstrated significant associations between dengue incidence and climatic variables (Benedum et al., 2018), population density (Lolo & Wiyono, 2023), and larva-free indices (Amelinda et al., 2022). Recent predictive models have demonstrated high accuracy in identifying high-risk areas (Andrade Girón et al., 2025; Dom et al., 2025; Xie et al., 2025). However, in practice, dengue prevention efforts are often hindered by fragmented data, limited integration of environmental and epidemiological indicators, and the lack of accessible, real-time risk information for local decision-makers and communities. Their integration into operational early warning systems remains limited, particularly at the urban scale.

This study develops an integrated early detection model for dengue susceptibily in Pontianak City by combining climate factors and LFI. By generating spatially explicit and accessible risk information, this approach aims to strengthen early warning capacity and support timely, targeted, and evidence-based dengue prevention strategies in rapidly urbanizing tropical environments.

2. RESEARCH METHOD

This study employed an observational analytical design with a cross-sectional approach to examine the association between climate parameters, population density, and Larvae-Free Index (LFI) as independent variables, while dengue fever incidence rate served as the dependent variable. Pontianak City was selected due to its tropical climate, high population density, and persistent dengue transmission.

Both primary and secondary data were utilised in this study. Primary data were collected using structured field recording sheets. Secondary data were obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG), the Central Statistics Agency of Pontianak City (BPS), and the Pontianak City Health Office. The dataset covered the period from 2022 to 2024 and was organised at the urban village (kelurahan) level in Pontianak. The study variables included monthly rainfall intensity (mm), relative humidity (%), population density (persons/km²), LFI (%), and dengue fever incidence rate (IR). Each parameter was assigned a score of 1 (high risk) or 2 (low risk) according to predefined thresholds (e.g., rainfall intensity ≤200 mm/month, humidity >80%, population density ≥ 64 person/km2, LFI ≥84%, and incidence rate ≥10 were classified as high risk).

Descriptive (univariate) analysis was conducted to summarize the distribution of all study variables, including rainfall intensity, relative humidity, population density, House Index, and dengue incidence rate. Bivariate analysis was performed using chi-square tests to assess the association between each independent variable and dengue incidence rate under a cross-sectional framework. To evaluate the combined effects of factors on dengue transmission, multivariate analysis was conducted using multiple logistic regression. Statistical significance was defined as a p-value < 0.05. All analyses were performed using standard statistical software. This study was approved by the Medical and Health Research Ethics Committee of the Faculty of Medicine, Public Health and Nursing at Universitas Gadjah Mada with Approval Letter No. KE/FK/0797/EC/2022.

3. RESULTS AND DISCUSSION

A total of 216 observations were analyzed, combining monthly data from 2022 to 2024 across all urban village in Pontianak.

Table 1. Rainfall Intensity, Humidity, Population Density, Larva-Free Index, and Dengue Incidence Rates From 2022 To 2024

Parameter	Mean	Minimum	Maximum
Rainfall	263.86	97	528
Relative Humidity	84.00	78	88
Population Density	76.2639	3041	9268
Larva-Free Index	6405.83	64.22	86.83
Incidence Rate	10.4472	00	58.88

Overall, the study area experienced relatively high rainfall intensity and humidity. Mean monthly rainfall intensity was 263.86 mm (range: 97–528 mm), and mean relative humidity was 84% (range: 78–88%). Population density varied widely across districts, while the larva-free index ranged from 16% to 89%, indicating substantial variation in vector control conditions. The average dengue incidence rate (IR) was 10.45, with a maximum value of 58.88, reflecting marked spatial and temporal heterogeneity in dengue transmission.

Bivariate analysis was conducted to assess the association between each risk factor and dengue incidence rate. Rainfall intensity and population density showed statistically significant relationships with dengue incidence. Areas with higher rainfall intensity were more likely to be classified as dengue-risk areas (p = 0.039), and higher population density was also significantly associated with increased dengue risk (p = 0.003). In contrast, relative humidity and the larva-free index did not show statistically significant associations with dengue risk at the bivariate level (p > 0.05), although areas with lower larva-free rates tended to have higher dengue incidence.

Table 2. Risk Factors of the Incidence Rate of Dengue Fever.

	Incidence Rate of Dengue Fever							
Variable	High Risk		Low Risk		Total		P-Value	COR
	n	%	n	%	N	%		
Larvae-Free Index								
High Risk	73	38.0	119	62.0	192	100	0.047*	3.067
Low Risk	4	16.7	20	83.3	24	100		(1.008-9.329)
Relative Humidity								
High Risk	69	34.2	133	65.8			0.148	0.389

Low Risk	8	57.1	6	42.9				(0.130-1.166)
Rainfall								
High Risk	60	40.5	88	59.5	148	100	0.039*	2.045
Low Risk	17	25.0	51	75.0	68	100		(1.079 – 3.877)
Population Density								
High Risk	37	34.3	71	65.7	108	100	0.776	0.886
Low Risk	40	37.0	68	63.0	108	100		(0.507-1.547)

Multivariate logistic regression was used to identify the most influential predictors after controlling for other variables. In the final model, rainfall intensity and the larva-free index remained significant predictors of dengue vulnerability. Higher rainfall intensity ncreased the likelihood of dengue occurrence (p = 0.025), while lower larva-free rates were also significantly associated with higher dengue risk (p = 0.042). Other variables did not retain significance in the adjusted model.

Table 3. Predictive Model of Dengue Fever Incidence Rate

Predictors	**Coef. B**	**SE**	**p-Value**	**AOR (95% CI)**
Rainfall Intensity	0.740	0.329	0.025	2.097 (1.100 – 3.398)
LFI	0.012	0.006	0.042	1.102 (1.000 – 1.023)
Constant*	-1.631	0.769	0.034	-

Table 4 presents the results of a predictive regression model examining the association between rainfall intensity, LFI, and dengue fever incidence rate. The analysis shows that rainfall intensity is a statistically significant predictor of dengue incidence (AOR=2.097; 1.100–3.398) indicates that for every unit increase in rainfall intensity, the odds of dengue incidence increase by approximately 2.1 times, holding other variables constant. Similarly, LFI is also a significant predictor (AOR = 1.102; 1.000–1.023) suggests that each unit increase in LFI is associated with a slight increase in the odds of dengue incidence. Overall, both rainfall intensity and LFI are statistically significant factors influencing dengue fever incidence in the model, with rainfall demonstrating a stronger effect size compared to LFI. The formula to predict the dengue fever incidence rate using the coefficients (β) can be shown below:

(i) $$p = -1.631 + 0.740(\text{Rainfall}) + 0.012(\text{LFI})$$ .... logistic regression equation

(ii) $$p = \frac{1}{1+e^{-(-1.631+0.740(rainfall)+0.012(LFI)}}$$ .... probability form

Where: p = probability of dengue fever incidence
rainfall = coded rainfall variable
LFI = coded larva-free index variable

The logistic regression results indicate that increases in rainfall intensity and changes in larval density significantly influence the probability of dengue transmission. This finding is biologically plausible because dengue transmission depends heavily on environmental conditions that support the breeding and survival of Aedes mosquitoes, the primary vectors of the dengue virus (Costa et al., 2022; Sureshkumar & Shekhar, 2025).

The association between rainfall intensity and dengue incidence underscores precipitation as a key pathway through which climate variability and climate change influence Aedes aegypti dynamics (Abbasi, 2025). This is also consistent with previous studies, which stated that higher rainfall intensity increased the likelihood of dengue occurrence (Cheng et al., 2023; Monintja et al., 2022). Moderate and sustained rainfall increases the availability of stagnant water in natural and artificial containers such as buckets, discarded tires, roof gutters, and water storage containers. These environments serve as ideal oviposition sites for Aedes aegypti. As breeding sites increase, larval survival improves, leading to higher adult mosquito density. An increase in adult mosquito population enhances human-vector contact, thereby increasing dengue transmission and incidence (Lin & Wen, 2024).

The role of population density highlights how rapid urbanisation amplifies climate-related dengue risk by increasing human–vector contact (Nakase et al., 2024). High population density also facilitates the spread of the disease, as the interaction between humans and mosquitoes becomes more frequent (Kolimenakis et al., 2021). From a policy perspective, this finding reinforces the need for dengue prevention strategies that are integrated into urban planning, housing, and sanitation policies, particularly in densely populated neighbourhoods (Alberto Montenegro-Quiñonez et al., 2023; Hoque et al., 2025). Although the LFI was not consistently significant in bivariate analysis, its contribution in the multivariate model indicates that routine entomological surveillance remains essential, especially during periods of high rainfall when vector populations can expand rapidly.

The Larva-Free Index (LFI) reflects the proportion of houses or containers free from mosquito larvae. A lower LFI indicates higher larval density, meaning more breeding sites are positive for Aedes larvae. High larval density directly contributes to increased adult mosquito populations, which raises the probability of virus transmission (Naura Qonita & Yusva Dwi Saputra, 2023). Larval density serves as a more proximal and immediate predictor of dengue risk compared to rainfall because it directly measures vector abundance (Dutra et al., 2024). While rainfall creates environmental conditions favorable for breeding, larval density reflects the actual entomological outcome of those conditions (Maretha et al., 2022). Therefore, areas with high rainfall but strong vector control measures may maintain a high LFI and consequently lower dengue incidence.

The vulnerability model developed in this study offers a practical early warning tool for public health decision-making (Cofone et al., 2025; Umar, 2023). While the model explains a limited proportion of overall variance, the sharply elevated predicted risk when high rainfall intensity coincides with low larva-free rates has clear operational value. Health authorities can use these combined indicators to trigger pre-emptive vector control measures, prioritise high-risk areas, allocate resources more efficiently, and intensify community-based interventions before outbreaks occur.

In the context of climate change, these findings support a shift from reactive outbreak response toward anticipatory, climate-informed dengue control. Integrating meteorological monitoring, vector surveillance, and demographic data into routine public health systems can strengthen preparedness and resilience at the city level (Hertelendy et al., 2025; Lugten & Hariharan, 2022). Such approaches align with broader climate and health adaptation goals and are essential to reducing the future health and economic burden of dengue in rapidly urbanising tropical regions.

This study has several limitations. First, the predictive model explains only a limited proportion of variance in dengue incidence, suggesting that other unmeasured environmental, socioeconomic, and behavioral factors may contribute to transmission dynamics. Second, the use of aggregated data may limit the ability to infer individual-level risk and introduce the possibility of ecological bias. Third, the findings are based on a specific urban tropical context, which may limit generalizability to other settings. Finally, the temporal scope of the data may not fully capture long-term climate variability associated with climate change.

Overall, the results of this study provide an important contribution to improving the dengue infection vulnerability information system that can be accessed by stakeholders and the community, in order to reduce the impact of the disease through an integrated predictive approach.

4. CONCLUSION

This study demonstrates that rainfall intensity and LFI are key determinants of dengue vulnerability in Pontianak City. The results confirm that rainfall density and LFI can serve as an effective tool for identifying high-risk areas and prioritizing intervention. Future development may focus on integrating real-time climate monitoring, digital-based surveillance, and spatial mapping to improve accessibility and responsiveness. Through these advancements, vulnerability information can be delivered more promptly and accurately, enabling communities and health authorities to conduct preventive measures such as source reduction, larviciding, and public awareness activities in a timelier and more focused manner.

REFERENCES

Abbasi E. (2025). The impact of climate change on travel-related vector-borne diseases: A case study on dengue virus transmission. Travel medicine and infectious disease, 65, 102841. https://doi.org/10.1016/j.tmaid.2025.102841

Abdullah, N. A. M. H., Dom, N. C., Salleh, S. A., Salim, H., & Precha, N. (2022). The association between dengue case and climate: A systematic review and meta-analysis. One health (Amsterdam, Netherlands), 15, 100452. https://doi.org/10.1016/j.onehlt.2022.100452

Montenegro-Quiñonez, C. A., Louis, V. R., Horstick, O., Velayudhan, R., Dambach, P., & Runge-Ranzinger, S. (2023). Interventions against Aedes/dengue at the household level: a systematic review and meta-analysis. EBioMedicine, 93, 104660. https://doi.org/10.1016/j.ebiom.2023.104660 https://doi.org/https://doi.org/10.1016/j.ebiom.2023.104660

Amelinda, Y. S., Wulandari, R. A., & Asyary, A. (2022). The effects of climate factors, population density, and vector density on the incidence of dengue hemorrhagic fever in South Jakarta Administrative City 2016-2020: an ecological study. Acta bio-medica : Atenei Parmensis, 93(6), e2022323. https://doi.org/10.23750/abm.v93i6.13503

Anas, A. S., Wulandari, N. A., & Anas, H. R. (2025). Faktor Risiko Penyakit Demam Berdarah Dengue. Jurnal Kolaboratif Sains, 8(6), 3169-3176. Retrived : https://www.jurnal.unismuhpalu.ac.id/index.php/JKS/article/view/7913

Andrade Girón, D. C., Marín Rodriguez, W. J., Lioo-Jordan, F. D. M., & Ausejo Sánchez, J. L. (2025, February). Machine learning and deep learning models for dengue diagnosis prediction: A systematic review. In Informatics (Vol. 12, No. 1, p. 15). MDPI. https://doi.org/10.3390/informatics12010015

Aulia, S. S. (2020). Lembar Hasil Penilaian Sejawat Sebidang Atau Peer Review Karya Ilmiah : Jurnal Ilmiah. Repository Universitas Bina Sarana Informatika (RUBSI), 2(April), 1–2.

Benedum, C. M., Seidahmed, O. M. E., Eltahir, E. A. B., & Markuzon, N. (2018). Statistical modeling of the effect of rainfall flushing on dengue transmission in Singapore. PLoS neglected tropical diseases, 12(12), e0006935. https://doi.org/10.1371/journal.pntd.0006935

Caldwell, J. M., LaBeaud, A. D., Lambin, E. F., Stewart-Ibarra, A. M., Ndenga, B. A., Mutuku, F. M., Krystosik, A. R., Ayala, E. B., Anyamba, A., Borbor-Cordova, M. J., Damoah, R., Grossi-Soyster, E. N., Heras, F. H., Ngugi, H. N., Ryan, S. J., Shah, M. M., Sippy, R., & Mordecai, E. A. (2021). Climate predicts geographic and temporal variation in mosquito-borne disease dynamics on two continents. Nature communications, 12(1), 1233. https://doi.org/10.1038/s41467-021-21496-7.

Cheng, Q., Jing, Q., Collender, P. A., Head, J. R., Li, Q., Yu, H., Li, Z., Ju, Y., Chen, T., Wang, P., Cleary, E., & Lai, S. (2023). Prior water availability modifies the effect of heavy rainfall on dengue transmission: a time series analysis of passive surveillance data from southern China. Research square, rs.3.rs-3302421. https://doi.org/10.21203/rs.3.rs-3302421/v1

Cofone, L., Sabato, M., Di Paolo, C., Di Giovanni, S., Donato, M. A., & Paglione, L. (2025). Urban, architectural, and socioeconomic factors contributing to the concentration of potential arbovirus vectors and arbovirosis in urban environments from a one health perspective: A systematic review. Sustainability, 17(9), 4077. https://doi.org/10.3390/su17094077

Costa, A. C., Gomes, T. F., Moreira, R. P., Cavalcante, T. F., & Mamede, G. L. (2022). Influence of hydroclimatic variability on dengue incidence in a tropical dryland area. Acta tropica, 235, 106657. https://doi.org/10.1016/j.actatropica.2022.106657

Dinkes Kalbar, 2024. (2024). Profil Kesehatan Kalbar 2024. Profil Kesehatan 2024, 16(2), 39–55.

Dom, N. C., Abdullah, N. A. M. H., Dapari, R., & Salleh, S. A. (2025). Fine-scale predictive modeling of Aedes mosquito abundance and dengue risk indicators using machine learning algorithms with microclimatic variables. Scientific reports, 15(1), 37017. https://doi.org/10.1038/s41598-025-17191-y

Dutra, H. L. C., Marshall, D. J., Comerford, B., McNulty, B. P., Diaz, A. M., Jones, M. J., Mejia, A. J., Bjornstad, O. N., & McGraw, E. A. (2024). Larval crowding enhances dengue virus loads in Aedes aegypti, a relationship that might increase transmission in urban environments. PLoS neglected tropical diseases, 18(9), e0012482. https://doi.org/10.1371/journal.pntd.0012482

Hertelendy, A. J., Dresser, C., Gorgens, S., Hertelendy, A. P., Biddinger, P. D., & Ciottone, G. (2025). Strengthening healthcare system resilience: a comprehensive framework for tropical cyclone preparedness and response. Lancet regional health. Americas, 48, 101205. https://doi.org/10.1016/j.lana.2025.101205

Hoque, M. A. A., Sardar, M. L., Mukul, S. A., & Pradhan, B. (2025). Mapping dengue susceptibility in Dhaka city: a geospatial multi-criteria approach integrating environmental and demographic factors. Spatial Information Research, 33(4), 33. https://doi.org/10.1007/s41324-025-00635-y

Kolimenakis, A., Heinz, S., Wilson, M. L., Winkler, V., Yakob, L., Michaelakis, A., Papachristos, D., Richardson, C., & Horstick, O. (2021). The role of urbanisation in the spread of Aedes mosquitoes and the diseases they transmit-A systematic review. PLoS neglected tropical diseases, 15(9), e0009631. https://doi.org/10.1371/journal.pntd.0009631

Lahondère, C., Vinauger, C., Liaw, J. E., Tobin, K. K. S., Joiner, J. M., & Riffell, J. A. (2023). Effect of Temperature on Mosquito Olfaction. Integrative and comparative biology, 63(2), 356–367. https://doi.org/10.1093/icb/icad066

Lin, C. H., & Wen, T. H. (2024). Assessing the impact of emergency measures in varied population density areas during a large dengue outbreak. Heliyon, 10(6), e27931. https://doi.org/10.1016/j.heliyon.2024.e27931

Lolo, W. A., & Wiyono, W. I. (2023). Peningkatan Kapasitas Masyarakat Dalam Upaya Pencegahan Demam Berdarah Dengue (DBD) Melalui Pelatihan Pembuatan Bio Spray Anti Nyamuk Di Kelurahan Mapanget Kecamatan Talawaan Kabupaten Minahasa Utara. The Studies of Social Sciences, 5(2), 41-51. https://doi.org/10.35801/tsss.v5i2.51692

Lugten, E., & Hariharan, N. (2022). Strengthening Health Systems for Climate Adaptation and Health Security: Key Considerations for Policy and Programming. Health security, 20(5), 435–439. https://doi.org/10.1089/hs.2022.0050

Mamenun, Koesmaryono, Y., Sopaheluwakan, A., Hidayati, R., Dasanto, B. D., & Aryati, R. (2024). Spatiotemporal Characterization of Dengue Incidence and Its Correlation to Climate Parameters in Indonesia. Insects, 15(5), 366. https://doi.org/10.3390/insects15050366

Maretha, L., Razak, R., & Faisya, A. F. (2022). The Relation between Rainfall and Larval Density of Dengue Hemorrhagic Fever with Spatial Modeling. Media Kesehatan Masyarakat Indonesia, 18(1), 10-17. https://doi.org/10.30597/mkmi.v18i1.18388

Monintja, T. C., Arsin, A. A., Syafar, M., & Amiruddin, R. (2022). Relationship between rainfall and rainy days with dengue hemorrhagic fever incidence in Manado City, North Sulawesi, Indonesia. Open Access Macedonian Journal of Medical Sciences, 10(E), 840-843. https://doi.org/10.3889/oamjms.2022.8897

Nakase, T., Giovanetti, M., Obolski, U., & Lourenço, J. (2024). Population at risk of dengue virus transmission has increased due to coupled climate factors and population growth. Communications Earth & Environment, 5(1), 475. https://doi.org/10.1038/s43247-024-01639-6

Naura Qonita, & Yusva Dwi Saputra. (2023). Relationship between Larva Free Index (LFI) and healthy house with DHF incidence rate in Banyuwangi Regency, 2022. World Journal of Advanced Research and Reviews, 18(2), 1372–1378. https://doi.org/10.30574/wjarr.2023.18.2.0979

Nosrat, C., Altamirano, J., Anyamba, A., Caldwell, J. M., Damoah, R., Mutuku, F., Ndenga, B., & LaBeaud, A. D. (2021). Impact of recent climate extremes on mosquito-borne disease transmission in Kenya. PLoS neglected tropical diseases, 15(3), e0009182. https://doi.org/10.1371/journal.pntd.0009182

Nugraheni, W. P., Nuraini, S., Garjito, T. A., Pawitaningtyas, I., Lestyoningrum, S. D., Putri, L. M., Nursafingi, A., Kusnali, A., Noveyani, A. E., & Dhewantara, P. W. (2026). Assessing the epidemiological and economic impact of dengue from 1990 to 2021 in Indonesia. Clinical Epidemiology and Global Health, 38, 102303. https://doi.org/10.1016/j.cegh.2026.102303

Sureshkumar, S., & Shekhar, S. (2025). Impact of urban heat island effect on dengue incidence: a remote sensing approach using thermal and high-resolution optical imagery. BMC public health, 25(1), 2914. https://doi.org/10.1186/s12889-025-23763-4

Umar, F. (2023). Integrated Public Health Strategies for Vector Control in the Context of Climate Change and Urbanization. Jurnal Riset Kualitatif dan Promosi Kesehatan, 2(1), 15-26. https://doi.org/10.61194/jrkpk.v2i1.660

Xie, Y., Wang, B., Chen, Q., Wei, H., Ke, Y., Xie, F., Guan, X., Rui, J., & Chen, T. (2025). Forecasting high-risk areas for dengue outbreaks in China: A trend analysis of Aedes albopictus and Aedes aegypti distributions from 2014 to 2030. PLOS Neglected Tropical Diseases, 2025-July. https://doi.org/10.1371/journal.pntd.0013237

Yang, Z. S., Baua, A. D., Hemdan, M. S., Assavalapsakul, W., Wang, W. H., Lin, C. Y., Chao, D. Y., Chen, Y. H., & Wang, S. F. (2025). Dengue virus infection: A systematic review of pathogenesis, diagnosis and management. Journal of infection and public health, 18(12), 102982. https://doi.org/10.1016/j.jiph.2025.102982

Zhang, W. X., Zhao, T. Y., Wang, C. C., He, Y., Lu, H. Z., Zhang, H. T., Wang, L. M., Zhang, M., Li, C. X., & Deng, S. Q. (2025). Assessing the global dengue burden: Incidence, mortality, and disability trends over three decades. PLoS neglected tropical diseases, 19(3), e0012932. https://doi.org/10.1371/journal.pntd.0012932