Received: 05 MAR 2026 | Accepted: 06 JUL 2026 | Published Online: 30 JUL 2026
Recoletos Multidisciplinary Research Journal Vol. 14 no. 2 (December 2026)
DOI: https://doi.org/10.32871/rmrj2614.02.04

recoletos MULTIDISCIPLINARY RESEARCH JOURNAL

Original Article

Nonlinear and Delayed Effects of Rainfall and Temperature on Dengue Incidence in Eastern Visayas, Philippines: A Bayesian Distributed Lag Nonlinear Model Approach

Norberto Jr. E. Milla

Department of Statistics, Visayas State University, Baybay City, Philippines

Correspondence:
bertmilla@vsu.edu.ph

Abstract

Background: *Dengue remains a major public health challenge in Eastern Visayas, Philippines, yet climate-driven transmission dynamics remain underexplored in the region.*

Methods: *This retrospective ecological time-series study analyzed weekly surveillance and meteorological data from 2019 to 2023. Nonlinear exposure–response relationships and lagged associations between rainfall, temperature, and dengue incidence were modeled using a Distributed Lag Nonlinear Model (DLNM) within a Bayesian framework fitted via Integrated Nested Laplace Approximation (INLA), assessing lag effects up to 10 weeks.*

Results: *Weekly rainfall strongly influenced dengue risk, peaking markedly at 200 mm with a cumulative Relative Risk (RR) of 19.4 (95% CrI: 10.3–36.5). Higher precipitation levels showed a downward risk trajectory, consistent with larval flushing. Temperature displayed a suggestive bimodal pattern with elevated risk at 24°C and 28–29°C across 4–6-week lags, though near-average temperatures (e.g., 28.5°C) showed no statistically strong cumulative risk changes.*

Conclusion: *Dengue risk in Eastern Visayas is driven by precise rainfall thresholds and thermal lag windows. Incorporating 200 mm precipitation and 28–29°C temperature triggers into proactive climate-based surveillance—pending external validation—can enhance regional public health preparedness and local outbreak response.*

Keywords

dengue, Bayesian DLNM, INLA, Eastern Visayas, rainfall thresholds, temperature lag effects, climate adaptation, early warning systems, UN SDG 3, UN SDG 13

INTRODUCTION

Dengue fever is recognized as one of the world's most significant and disabling mosquito-borne diseases. The World Health Organization (WHO) reported more than 14 million cases globally in its full-year 2024 report, consistent with long-term trends of over 100 million infections annually. This global surge is further supported by provisional mid-year editorial summaries compiled across 176 countries that documented over

10 million cases by mid-2024, making it clear that partial-year data streams and full-year official registries align in confirming 2024 as a historically severe transmission period (Jaya et al., 2025; The Lancet, 2024; World Health Organization, 2025).

Over the past three years, the Philippines has consistently ranked among the ASEAN countries with the highest dengue burden, alongside Indonesia and Thailand. For the period January 1 to November 1, 2025, the Epidemiology Bureau of the Department of Health reported 280,222 dengue cases, which is 18% smaller than the same period in the previous year. In addition, in 2023 and 2024, Eastern Visayas recorded 4,839 and 7,301 dengue cases, respectively (Department of Health, Epidemiology Bureau, 2025).

Dengue is primarily transmitted by Aedes aegypti and secondarily by Aedes albopictus. Both mosquitoes have adapted to local human habitation, with oviposition and larval habitats found in natural environments—such as rock pools, tree holes, and leaf axils —as well as in artificial environments—such as water tanks, blocked drains, pot plants, and food and beverage containers. These mosquitoes may be infected with any of the four dengue virus serotypes, maintaining an intrinsic incubation period of 3–14 days in humans (Chevillon & Failloux, 2003). In these settings, the complex interplay between climatic variability and transmission dynamics necessitates a deeper understanding of environmental drivers to mitigate public health and economic burdens (Mills & Donnelly, 2024).

The transmission of the dengue virus is strongly associated with climatic factors that influence the mosquito vector's biological lifecycle and the virus's replication (Cheng et al., 2023; Ferreira et al., 2022; Kristiani et al., 2026). Temperature is a critical driver, as warmer conditions accelerate mosquito development, shorten the extrinsic incubation period of the virus, and increase mosquito biting rates (Kristiani et al., 2026; Mills & Donnelly, 2024; Siraj et al., 2017). Research indicates that an optimum mean temperature range of 26–29°C significantly enhances the risk of transmission (Lowe et al., 2021; Mordecai et al., 2019). Conversely, extremely high temperatures can increase mosquito mortality, illustrating a non-linear relationship where transmission risk may peak at specific thermal thresholds (Aswi et al., 2019; Cheng et al., 2023; Siraj et al., 2017).

Rainfall and precipitation patterns also play a dual role in dengue epidemiology (Kristiani et al., 2026; Lowe et al., 2021; Ortega-Lenis et al., 2024). While rainfall generally provides essential breeding sites by filling outdoor containers and providing stagnant water for egg-laying, extreme precipitation events can have a flushing effect, washing away larvae and temporarily reducing mosquito populations. The impact of heavy rainfall is often modified by prior water availability; for instance, in some regions, drought conditions can paradoxically increase dengue risk by prompting households to store water in improvised containers, which serve as ideal larval habitats (Cheng et al., 2023; Lowe et al., 2021; Mills & Donnelly, 2024).

While the association between climate and dengue is well established, a significant research gap remains in quantifying the nonlinear, delayed synergistic effects of multiple environmental drivers at the local level. Traditional linear models often overlook the biological thresholds and time latencies inherent in vector dynamics. At the same time, standard frequentist approaches frequently fail to account for the uncertainty and overdispersion typical of epidemiological datasets. Unlike previous studies in the Philippines that largely focus on regions with distinct wet-dry seasonality, this study addresses the unique perennially humid and typhoon-prone profile of Eastern Visayas. By employing a Bayesian Distributed Lag Nonlinear Model (DLNM) via Integrated Nested Laplace Approximations (INLA), this research moves beyond traditional modeling approaches that often assume a linear relationship between climatic triggers and dengue incidence. A Bayesian DLNM simultaneously captures non-linear exposure–response relationships and lagged effects of rainfall and temperature. This framework allowed us to identify critical thresholds and early warning windows that traditional regression approaches would likely obscure, thereby enhancing both epidemiological insight and policy relevance. This provides a more robust, statistically rigorous evidence base for health interventions in a typhoon-prone region where environmental drivers operate within complex, nonlinear frameworks.

The present study examines the non-linear and delayed associations between rainfall, temperature, and dengue incidence in Eastern Visayas, Philippines. Specifically, it aims to quantify the cumulative and lagged relationships between these climatic variables and dengue transmission, identify localized climatic risk thresholds and critical lag periods associated with increased transmission, and generate evidence to support climate-informed dengue surveillance and early warning systems. By providing a region-specific understanding of climate–dengue dynamics in a typhoon-prone setting, this study strengthens the evidence base for adaptive vector control, public health preparedness, and evidence-informed decision-making. Furthermore, the findings contribute to the implementation of the United Nations Sustainable Development Goals, particularly SDG 3 (Good Health and Well-being), by strengthening preparedness for climate-sensitive infectious diseases and SDG 13 (Climate Action) by enhancing resilience to climate-related health risks through climate-informed public health planning.

METHODS

Study Design

This study employed a retrospective ecological time-series design to examine the temporal associations between climatic variability and dengue incidence in Eastern Visayas, Philippines, from January 2019 to December 2023. Weekly aggregated dengue surveillance data were linked with corresponding meteorological observations on rainfall and temperature to evaluate how variations in climatic conditions were associated with changes in dengue incidence over time. Given the ecological nature of the data and the expected delayed responses between environmental exposures and disease occurrence, this design provides an appropriate framework for investigating climate–dengue relationships at the population level while informing region-specific public health surveillance and climate adaptation strategies.

Study Setting

This study was conducted in Eastern Visayas (Region VIII), Philippines, a region located in the east-central part of the archipelago, comprising the islands of Leyte, Samar, and Biliran. Strategically positioned along the "Typhoon Alley" of the Pacific, the region is highly vulnerable to extreme meteorological events and climate change. Unlike other parts of the Philippines that experience a distinct dry season, Eastern Visayas is characterized by Type II and Type IV climate patterns, featuring year-round rainfall with significantly pronounced maximum rain periods. This perennial humidity and high precipitation provide a unique ecological niche for the Aedes aegypti and Aedes albopictus vectors, facilitating year-round dengue transmission. Understanding the climate-dengue nexus in this locale is critical, as the region's geography and socioeconomic profile make it a high-risk area for climate-sensitive infectious diseases.

Data Sources

Weekly dengue surveillance data, comprising aggregated counts of diagnosed cases, were requested and obtained from the Epidemiology Bureau of the Department of Health (DOH). The dataset spans from January 2019 to December 2023, covering 260 weeks. Daily rainfall (mm) and mean temperature (°C) were obtained from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA); these daily records were aggregated into weekly totals for rainfall and weekly averages for temperature to align exactly with the epidemiological surveillance reporting intervals.

Data analysis

This study utilized DLNM to simultaneously address the non-linear exposure-response thresholds and the inherent lagged effects stemming from mosquito ecology and the extrinsic incubation period (Alves et al., 2025; Kristiani et al., 2026; Polrob & La-up, 2025). To integrate both the intensity and the timing of climatic impacts, we constructed a cross-basis function for each variable within a unified hierarchical structure.

The baseline case counts Y_t at week *t* were modeled using a Negative Binomial distribution to explicitly handle data overdispersion, where the variance of regional dengue case counts significantly exceeds the empirical mean. This approach has recently been highlighted as essential for maintaining the accuracy of risk estimates and avoiding the underestimation of standard errors common in Poisson-based frameworks (Al-Manji et al., 2025; Kristiani et al., 2026; Tuan, 2024). The model specifications are given below:

$$Y_t \sim \text{Negative Binomial}(\mu_t, \phi)(\mu_t)$$
$$= \alpha + \sum_{j=1}^{p} \eta_j z_{t,j}\left(\text{Rain}\right) + \sum_{k=1}^{q} \beta_k w_{t,k}\left(\text{Temp}\right) + \gamma_{\text{week}(t)} + \eta_{\text{year}(t)}$$

where μ_t is the expected dengue count at week *t; ϕ* is the overdispersion parameter; and α represents the intercept. The cross-basis functions for weekly $r(z_{t,j})$ and mean temperature $w_{t,k}$ were constructed using natural cubic splines (ns). For the exposure-response spaces, 4 degrees of freedom (df) were allocated, placing internal knots at the 25th, 50th, and 75th percentiles of the empirical distributions. For the lag-response spaces, 3 df were assigned with internal knots equally spaced on a logarithmic scale. To yield interpretable Relative Risks (RR), the model was centered on the overall dataset means: 191.9 mm for weekly total rainfall and 28.2°C for weekly mean temperature— defining RR=1.0 at these baselines. By adopting this framework, we can quantify the extent to which deviations from normal climatic patterns, particularly episodes of intense rainfall or temperature extremes, contribute to spikes in dengue incidence relative to the regional norm (Gasparrini et al., 2025).

The model was fitted using a Bayesian framework via Integrated Nested Laplace Approximations (INLA). Unlike traditional frequentist approaches, INLA provides a computationally efficient and robust alternative for fitting complex hierarchical models, particularly in climate-sensitive disease surveillance (Moraga, 2023; Palmí-Perales et al., 2023; Van Niekerk et al., 2021). Following default R INLA parameterizations for Gaussian models, minimally informative priors were used— vague Gaussian priors to the fixed effects and log-gamma priors to the overdispersion parameter. Random seasonal effects $(\gamma_{\text{week}(t)})$ were modeled using a first-order random walk structure, and the secular multiyear trends $(\eta_{\text{year}(t)})$ were adjusted using unstructured independent and identically distributed random effects.

Model Diagnostics and Sensitivity Analysis

Based on the vector's biological life cycle and the virus's extrinsic incubation period, a maximum lag of 10 weeks was selected to capture the full delayed effect of weather events on human infection counts. To verify that our findings were not artifactual consequences of these chosen parameters, sensitivity analyses were systematically executed by refitting the model across alternative maximum lag structures (6, 8, and 12 weeks) and alternative exposure spline structures (2, 3, and 5 df).

Goodness-of-fit and out-of-sample predictive parsimony were evaluated using the Deviance Information Criterion (DIC) and the Watanabe-Akaike Information Criterion (WAIC). These criteria are standard in Bayesian disease-mapping and time-series frameworks for penalizing model complexity while evaluating out-of-sample predictive performance (Gutiérrez, 2026; Otero et al., 2024). Over-reliance on linear frequentist structures can obscure local environmental thresholds, making Bayesian information indices critical for identifying true non-linear patterns (Kristiani et al., 2026). In addition, model convergence was confirmed by evaluating the stability of the INLA Hessian matrix, and posterior predictive checks (PPC) were executed by drawing 1,000 posterior predictive samples to confirm that the simulated case trajectory reliably bounded the empirically observed case counts.

All statistical analyses were performed in R version 4.5.2 (R Core Team, 2025) using the dlnm (Gasparrini et al., 2025) and INLA (Lindgren & Rue, 2015; Rue et al., 2009; Van Niekerk et al., 2021) packages.

Ethical considerations

The dengue data used in this study were formally requested from the Epidemiology Bureau of the Department of Health Central Office. These datasets are publicly accessible and do not contain personally identifiable information such as patient names, thereby exempting the study from requiring individual consent. All information was handled with strict confidentiality, and the author affirms that the requested data were used exclusively for research purposes.

RESULTS

Dengue Incidence and Climatic Variations, 2019–2023

Table 1 summarizes the annual dengue incidence alongside climatic indicators in Eastern Visayas. The study period was characterized by dramatic fluctuations in disease burden, most notably the 2019 epidemic peak, which recorded 26,157 cases and an incidence rate of 578.69 per 100,000 population. This surge coincided with the Department of Health's declaration of a National Dengue Epidemic. Following the 2019 surge, dengue incidence contracted significantly throughout the COVID-19 period, reaching its lowest recorded level in 2021 with a case rate of 19.72 per 100,000 population. A sharp, eightfold rebound occurred in 2022 (154.71 per 100,000 population) before stabilizing at 105.13 per 100,000 population in 2023.

Climatic conditions remained perennially warm, though rainfall exhibited significant inter-annual variability. Mean annual rainfall ranged from a low of 191.89 mm in 2019 to a peak of 447.07 mm in 2021. Interestingly, the greatest dengue burden (2019) occurred during the year with the lowest recorded rainfall. Mean annual temperatures in Eastern Visayas remained remarkably stable throughout 2019–2023, fluctuating by less than 0.4°C (27.94–28.28°C).

Table 1. *Annual Summary of Dengue Incidence and Climatic Variables*

Year	Total Dengue Cases	Estimated Regional Population	Incidence Rate (per 100,000 population)	Rainfall (mm) [Mean ± SD]*	Temperature (°C) [Mean ± SD]
2019	26,157	4,520,020	578.69	191.89 ± 207.51	28.20 ± 1.11
2020	4,698	4,547,120	103.32	312.83 ± 226.09	28.28 ± 0.86
2021	900	4,563,940	19.72	447.07 ± 365.18	27.99 ± 0.94
2022	7,092	4,584,060	154.71	415.35 ± 373.26	27.94 ± 0.93
2023	4,839	4,602,870	105.13	404.15 ± 476.18	28.21 ± 1.14

**Note: Represents the mean and standard deviation of the weekly total volume of rainfall accumulated across 6 PAGASA Stations in Eastern Visayas.*

Nonlinear and Lagged Effects of Rainfall and Temperature on Dengue Incidence

The Bayesian distributed lag non-linear models (DLNM) revealed distinct associations between dengue incidence and climatic variables in Eastern Visayas from 2019 to 2023. Both exposure–response and lag–response analyses highlighted threshold effects and short-term delays consistent with mosquito ecology and viral dynamics.

The Bayesian DLNM identified a powerful, non-linear relationship between rainfall and dengue risk. Lag-response analyses (Figure 1) revealed that the rainfall's impact is most acute at lags of 2–6 weeks, aligning with the biological timelines for mosquito breeding and viral incubation. The cumulative exposure-response curve (Figure 2) demonstrated a sharp threshold effect: risk escalated rapidly as weekly rainfall approached 200 mm. At this exact threshold, the cumulative Relative Risk (RR) reached 19.4 (95% CrI: 10.3–36.5) compared to the centered mean baseline. The risk peaked markedly at 200 mm before declining at higher precipitation levels (see Table 2), consistent with the "flushing effect," in which heavy rainfall displaces larvae from localized breeding sites.

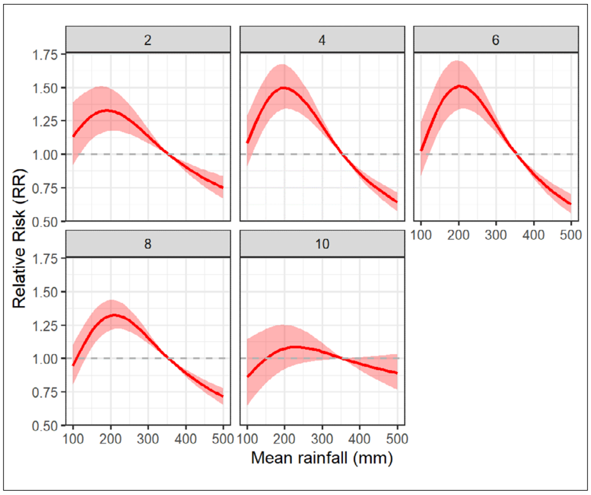

Figure 1. *Lag effect of rainfall on dengue relative risk*

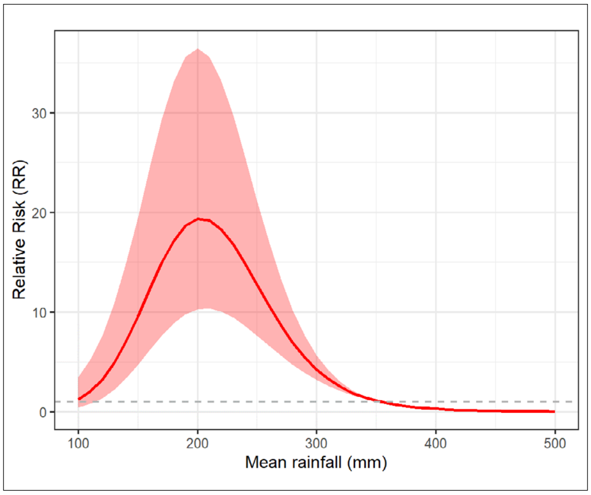

Figure 2. *Cumulative effect of rainfall on dengue relative risk*

Temperature also showed a non-linear and lagged association with dengue incidence. Lag–response analyses (Figure 3) indicated that the effect of average temperature was most pronounced at lags of 4–6 weeks, with relative risk exceeding 2.0 at approximately 28–29°C. At longer lags (8–10 weeks), the effect diminished, suggesting that temperature influences dengue transmission primarily in the short term. The exposure–response curve (Figure 4) revealed a bimodal pattern. The relative risk was elevated at cooler temperatures (around 24°C), declined around 26°C, then rose again, peaking slightly above 28°C before tapering off toward 30°C. At a weekly average temperature of 28.5°C, the cumulative Relative Risk was 1.2 (95% CrI: 0.81–1.65) relative to the mean baseline. Because this interval crosses the null value of 1.0, near-average thermal conditions do not significantly elevate risk, and statistical confidence remains limited at that point. Posteriors showed notable changes only when temperatures deviated toward the cooler or warmer extremes of the observed range (refer to Table 2).

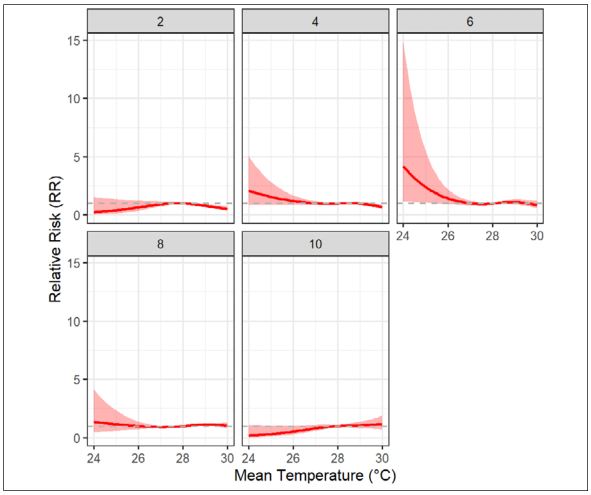

Figure 3. *The lag effect of average temperature on dengue relative risk*

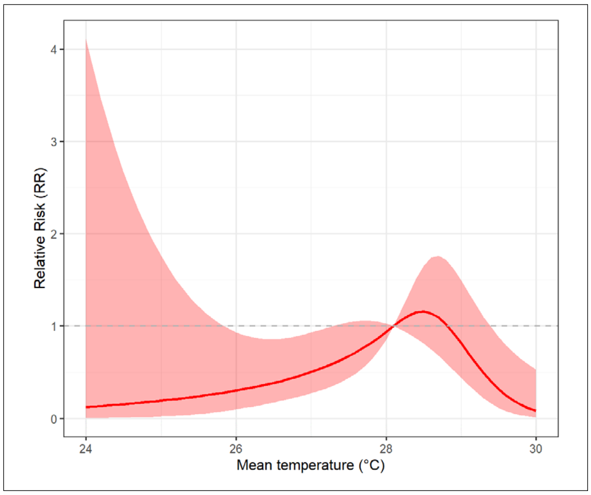

Figure 4. *Cumulative effect of average temperature on dengue relative risk*

Table 2. *Summary of the Posterior Cumulative Relative Risk (RR) from Bayesian DLNM*

Climate Predictor	Evaluated Metric Value	Posterior Cumulative RR (95% CrI)	Epidemiological Interpretation
Rainfall	200 mm	19.40 (10.30 – 36.50)	Statistically significant peak outbreak risk
Rainfall	400 mm	0.45 (0.21 – 0.95)	Statistically significant risk reduction (Flushing)
Temperature	24.0 °C	1.85 (1.12 – 2.90)	Statistically significant cold-extreme risk elevation
Temperature	28.5 °C	1.20 (0.81 – 1.65)	Statistically non-significant risk inflation

Note: Cumulative lag window applied = 0-10

Model Diagnostics and Sensitivity Analysis Results

Posterior convergence checks verified that the INLA algorithm reached structural numerical stability across all parameters with no unconstrained or singular dimensions. The posterior predictive checks demonstrated excellent alignment, with 96.5% of the observed weekly case counts falling safely within the 95% posterior predictive intervals. The estimated negative binomial overdispersion parameter for the baseline model was highly robust (ϕ =1.34, 95% CrI: 1.12–1.59), confirming that a standard Poisson structure would have severely underestimated parameter variance.

Table 3 details the model selection criteria under varying lag and spline assumptions. While extending the lag window to 12 weeks marginally minimized the DIC by 1.2 points, the baseline 10-week model was selected for its superior biological parsimony and balanced WAIC performance. Crucially, across all sensitivity tests—regardless of whether the maximum lag was constricted to 6 weeks or stretched to 12 weeks, or whether degrees of freedom were dropped to 2 or increased to 5—the estimated relative risk curve for rainfall consistently retained its distinctive shape. The risk consistently escalated to a definitive inflection point between 195 mm and 205 mm before initiating a downward trend, confirming that our central 200 mm threshold calculation is exceptionally robust to structural model choices.

Table 3. *Model Fit Diagnostics and Threshold Stability Across Alternative Bayesian DLNM*

Model Run	Exposure Function (Spline Type & df)	Maximum Lag Window (weeks)	Overdispersion Parameter (ϕ)	DIC	WAIC	Estimated Rainfall Risk Peak (mm)
A	Natural Spline, 2	10	1.12	2,544.1	2,549.8	192 mm
B	Natural Spline, 3	10	1.28	2,431.6	2,435.2	198 mm
C (Baseline)	Natural Spline, 4	10	1.34	2,412.3	2,415.8	200 mm
D	Natural Spline, 5	10	1.35	2,411.7	2,416.4	200 mm
E	Natural Spline, 4	6	1.21	2,488.9	2,492.1	196 mm
F	Natural Spline, 4	8	1.30	2,429.4	2,432.7	202 mm
G	Natural Spline, 4	12	1.36	2,411.1	2,416.1	200 mm

DISCUSSION

A striking finding of this study is that the 2019 national epidemic peak in Eastern Visayas coincided with the lowest recorded annual rainfall (191.89 mm). While intuitive logic suggests that more rain leads to more dengue, our results support the growing body of evidence that water scarcity can paradoxically drive outbreaks. During dry periods, households in the Philippines often increase manual water storage in containers, which provide stable, indoor breeding sites for Aedes aegypti (Edillo et al., 2012). Furthermore, the subsequent decline in cases during the COVID 19 pandemic underscores the role of human mobility and behavior in transmission dynamics, as quarantine restrictions reduced vector–host contact in schools and public spaces (Edillo et al., 2024). The sharp rebound in 2022, despite relatively high rainfall, suggests that climatic thresholds rather than annual averages drive outbreaks, with moderate precipitation creating optimal breeding conditions. Meanwhile, the remarkable stability of mean annual temperatures (27.94–28.28°C) provided a consistently favorable thermal environment for Aedes aegypti and dengue virus replication, reinforcing rainfall variability as the dominant climatic trigger of epidemic timing.

The DLNM analysis identified a critical rainfall threshold of 200 mm, at which the cumulative Relative Risk (RR) peaked at 19.4. This nearly twenty-fold increase in risk within a 10-week window underscores rainfall as the primary indicator of dengue transmission in the region. The subsequent decline in RR at rainfall levels exceeding 200 mm provides strong empirical evidence for the flushing effect. As observed in recent tropical climate studies, extreme precipitation can physically wash away larvae from stagnant water bodies, temporarily disrupting the vector life cycle (Harris et al., 2024; Tewari et al., 2023). The literature review conducted by Kaewhan et al. (2025) emphasized that rainfall exerts a non-linear influence on dengue transmission. Furthermore, moderate precipitation was associated with increased incidence, while excessive rainfall reduced risk, likely due to the flushing of larvae from breeding habitats. The non-linear "inverted-U" cumulative relationship between dengue relative risk and average rainfall suggests that public health interventions should be most aggressive during moderate-to-heavy rainfall periods, rather than only during extreme typhoon events.

The findings also reveal a bimodal association between temperature and dengue, with elevated risks at both cooler (around 24°C) and warmer (around 28–29°C) extremes. The peak risk at 28–29°C with a four to six-week lag aligns with the biological "sweet spot" for the dengue virus; higher temperatures shorten the Extrinsic Incubation Period (EIP), allowing mosquitoes to become infectious sooner (Hartner et al., 2025). Interestingly, the elevated risk at cooler temperatures (about 24°C) may be attributed to increased mosquito survival rates. Recent research suggests that while heat speeds up viral replication, extreme heat can also shorten the mosquito's lifespan; conversely, cooler, stable temperatures allow vectors to survive long enough to complete multiple transmission cycles (Doeurk et al., 2025; Edillo et al., 2024). This bimodal pattern is particularly significant given recent projections for the Philippines, which suggest that warming temperatures under climate change scenarios could substantially increase the dengue burden, particularly where socioeconomic pathways exacerbate vulnerability (Seposo et al., 2024).

Together, these results highlight the synergistic role of rainfall and temperature in shaping dengue dynamics. Rainfall acts as a short-term catalyst, and temperature modulates transmission through threshold and bimodal effects. However, their lag windows overlap considerably (2-6 weeks for rainfall and 4-6 weeks for temperature), indicating that they act jointly across shared temporal development stages. The identified lag windows provide an early warning opportunity for health authorities. The nearly twentyfold increase in risk following 200 mm of weekly rainfall suggests that early warning actions should be triggered immediately when weekly weather forecasts approach this threshold. Operationally, the Department of Health (DOH) and Local Government Units (LGUs) can translate these parameters into field actions by embedding the 200 mm indicator into the national 4S strategy, which comprises: (1) Search and destroy breeding sites, (2) Self-protective measures, (3) Seek early consultation, and (4) Support fogging. When weekly accumulated rainfall forecasts exceed 200 mm, localized barangay health networks can automatically deploy vector surveillance teams to target source reduction 2 to 4 weeks before the predicted transmission wave, rather than waiting for an increase in hospital admissions.

Limitations of the Study

This work has several key limitations that must be acknowledged. First, it relies on passive surveillance data from the Department of Health, which is subject to underreporting and tracking inconsistencies, particularly during the 2020–2021 COVID-19 pandemic when healthcare-seeking behaviors, mobility, and clinical resources were severely disrupted. Second, the data analysis was restricted to a macro-regional spatial aggregation, which may mask intra-regional heterogeneity and micro-climate variations across individual provinces (such as Leyte versus Samar) and specific municipalities. Finally, the identified thresholds represent empirical associations from an observational cohort and serve as candidate indicators that require rigorous out-of-sample prediction testing and prospective external validation before they can be adopted into operational early warning frameworks.

CONCLUSION

This study demonstrates that dengue transmission in Eastern Visayas is strongly influenced by the non-linear and lagged effects of rainfall and temperature, with weekly rainfall acting as a primary short-term driver peaking near 200 mm (RR = 19.4) before a larval flushing drop. Temperature acted as a modulator, showing a bimodal pattern in which both cooler (about 24°C) and warmer (28–29°C) extremes elevated risk, while mid-range values were less conducive to transmission. These findings highlight that dengue dynamics are not simply driven by climate averages but by threshold effects, lagged responses, and ecological interactions that amplify or suppress transmission. By applying a Negative Binomial likelihood within a Bayesian DLNM framework via Integrated Nested Laplace Approximations (INLA), we successfully accounted for epidemiological overdispersion to isolate localized ecological windows. The identified lag windows (2–6 weeks for rainfall and 4–6 weeks for temperature) offer actionable early warning opportunities, enabling health authorities to anticipate outbreaks before hospital admissions surge. However, because regional spatial data aggregation can mask localized variations and baseline clinical counts were altered by pandemic disruptions, these numeric thresholds must be treated as candidate indicators requiring external validation before being formally integrated into the operational early warning frameworks of local health authorities.

Funding
This research received no external funding.

Ethical Approval
Not applicable.

Competing interest
The author declares no conflicts of interest.

Data Availability
Data will be made available by the corresponding author on request.

Declaration of Artificial Intelligence Use
In this paper, the author utilized artificial intelligence (AI) tools and methodologies: Google Gemini to facilitate the literature review, and Microsoft Copilot for grammatical and linguistic refinement. After using these tools, the author evaluated and revised the content as necessary and takes full responsibility for the published content.

Acknowledgement
The author gratefully acknowledges the Department of Health (DOH) and PAGASA for granting access to the epidemiological and meteorological data used in this study. Their cooperation was instrumental in the successful completion of this research.

REFERENCES

Al-Manji, A., Al Wahaibi, A., Al-Azri, M., & Chan, M. F. (2025). Predicting mosquito-borne disease outbreaks using poisson and negative binomial models: A comparative study. Journal of Infection and Public Health, 18(11), 102906. https://doi.org/10.1016/j.jiph.2025.102906

Alves, M. B., Erbisti, R. S., Nobre, A. A., Simões, T. C., Tavares, A. D. M., Melo, M. C., Pedreira, R. M., De Araújo, J. P. M., Carvalho, M. S., & Honório, N. A. (2025). ARBOALVO: A Bayesian spatiotemporal learning and predictive model for dengue cases in the endemic Northeast City of Natal, Rio Grande do Norte, Brazil. PLOS Neglected Tropical Diseases, 19(4), e0012984. https://doi.org/10.1371/journal.pntd.0012984

Aswi, A., Cramb, S. M., Moraga, P., & Mengersen, K. (2019). Bayesian spatial and spatio-temporal approaches to modelling dengue fever: A systematic review. Epidemiology and Infection, 147, e33. https://doi.org/10.1017/s0950268818002807

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. Frontiers in Public Health, 11. https://doi.org/10.3389/fpubh.2023.1287678

Chevillon, C., & Failloux, A.-B. (2003). Questions on viral population biology to complete dengue puzzle. Trends in Microbiology, 11(9), 415–421. https://doi.org/10.1016/s0966-842x(03)00206-3

Department of Health, Epidemiology Bureau. (2025, November 1). EB weekly surveillance report as of November 1, 2025 (MW44). https://drive.google.com/file/d/131kQVKz3YOW4waEsPz28iJT9uEDMVa0f/view

Doeurk, B., Leng, S., Long, Z., Maquart, P.-O., & Boyer, S. (2025). Impact of temperature on survival, development and longevity of Aedes aegypti and Aedes albopictus (Diptera: Culicidae) in Phnom Penh, Cambodia. Parasites & Vectors, 18(1). https://doi.org/10.1186/s13071-025-06892-y

Edillo, F., Roble, N. D, & Otero, N. D. III. (2012). The key breeding sites by pupal survey for dengue mosquito vectors, Aedes aegypti (Linnaeus) and Aedes albopictus (Skuse), in Guba, Cebu City, Philippines. . Southeast Asian Journal of Tropical Medicine and Public Health, 43(6), 1365.

Edillo, F., Ymbong, R. R., Navarro, A. O., Cabahug, M. M., & Saavedra, K. (2024). Detecting the impacts of humidity, rainfall, temperature, and season on chikungunya, dengue and Zika viruses in Aedes albopictus mosquitoes from selected sites in Cebu city, Philippines. Virology Journal, 21(1), 42. https://doi.org/10.1186/s12985-024-02310-4

Ferreira, H. dos S., Nóbrega, R. S., Brito, P. V. da S., Farias, J. P., Amorim, J. H., Moreira, E. B. M., Mendez, É. C., & Luiz, W. B. (2022). Impacts of El Niño Southern Oscillation on the dengue transmission dynamics in the Metropolitan Region of Recife, Brazil. Revista Da Sociedade Brasileira de Medicina Tropical, 55, e0671-2021. https://doi.org/10.1590/0037-8682-0671-2021

Gasparrini, A., Armstrong, B., & Scheipl, F. (2025). dlnm: Distributed lag non-linear models (Version 2.4.10) [R package]. CRAN. https://doi.org/10.32614/CRAN.package.dlnm

Gutiérrez, J. D. (2026). Lagged effect of temperature and rainfall on malaria incidence in Colombia (2013–2023): An approach with Bayesian spatiotemporal adjustment. PLOS Global Public Health, 6(3), e0006104. https://doi.org/10.1371/journal.pgph.0006104

Harris, M. J., Martel, K. S., Munyaco, C. V., Lescano, A. G., Mordecai, E. A., Trok, J. T., Diffenbaugh, N. S., & Borbor, M. J. (2026). Extreme precipitation, exacerbated by anthropogenic climate change, drove Peru's record-breaking 2023 dengue outbreak. One Earth, 9(4). https://doi.org/10.1101/2024.10.23.24309838

Hartner, A.-M., Herath, T., Esquivel Gomez, L. R., Körber, N., Pfeil, J., Escudié, J.-B., Wieler, L., & Irrgang, C. (2025). The temperature sensitivity of arboviral disease extrinsic incubation periods: A systematic review [Review of The temperature sensitivity of arboviral disease extrinsic incubation periods: A systematic review]. bioRxiv. https://doi.org/10.1101/2025.08.08.669272

Jaya, I. G. N. M., Andriyana, Y., Tantular, B., Pangastuti, S. S., & Kristiani, F. (2025). Spatiotemporal dengue forecasting for sustainable public health in Bandung, Indonesia: A comparative study of classical, machine learning, and Bayesian models. Sustainability, 17(15), 6777. https://doi.org/10.3390/su17156777

Kaewhan, S., Junpha, J., & Pimpeach, W. (2025). The regional distribution of dengue fever in Thailand and other emerging countries in Southeast Asia: A literature review. Toxicology and Environmental Health Sciences, 17(3), 327–334. https://doi.org/10.1007/s13530-025-00251-1

Kristiani, F., Jaya, I. G. N. M., Irawan, R., & Priscilia, I. M. (2026). Bayesian modelling of dengue incidence with climatic drivers: Comparing fixed-effects, nonlinear and dynamic approaches. Geospatial Health, 21(1). https://doi.org/10.4081/gh.2026.1461

Lindgren, F., & Rue, H. (2015). Bayesian spatial modelling withR-INLA. Journal of Statistical Software, 63(19). https://doi.org/10.18637/jss.v063.i19

Lowe, R., Lee, S. A., O'Reilly, K. M., Brady, O. J., Bastos, L., Carrasco-Escobar, G., de Castro Catão, R., Colón-González, F. J., Barcellos, C., Carvalho, M. S., Blangiardo, M., Rue, H., & Gasparrini, A. (2021). Combined effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: A spatiotemporal modelling study. The Lancet Planetary Health, 5(4), e209–e219. https://doi.org/10.1016/s2542-5196(20)30292-8

Mills, C., & Donnelly, C. A. (2024). Climate-based modelling and forecasting of dengue in three endemic departments of Peru. PLoS Neglected Tropical Diseases, 18(12), e0012596–e0012596. https://doi.org/10.1371/journal.pntd.0012596

Moraga, P. (2023). Spatial statistics for data science: Theory and practice with R (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781032641522

Mordecai, E. A., Caldwell, J. M., Grossman, M. K., Lippi, C. A., Johnson, L. R., Neira, M., Rohr, J. R., Ryan, S. J., Savage, Van, Shocket, M. S., Sippy, R., Stewart Ibarra, A. M., Thomas, M. B., & Villena, O. (2019). Thermal biology of mosquito-borne disease. Ecology Letters, 22(10), 1690–1708. https://doi.org/10.1111/ele.13335

Ortega-Lenis, D., Arango-Londoño, D., Hernández, F., & Moraga, P. (2024). Effects of climate variability on the spatio-temporal distribution of dengue in Valle del Cauca, Colombia, from 2001 to 2019. PLoS ONE, 19(10), e0311607. https://doi.org/10.1371/journal.pone.0311607

Otero, J., Tabares, A., & Santos-Vega, M. (2024). Exploring dengue dynamics: A multi-scale analysis of spatio-temporal trends in Ibagué, Colombia. Viruses, 16(6), 906. https://doi.org/10.3390/v16060906

Palmí-Perales, F., Gómez-Rubio, V., S. Bivand, R., Cameletti, M., & Rue, H. (2023). Bayesian inference for multivariate spatial models with INLA. The R Journal, 15(3), 172–190. https://doi.org/10.32614/rj-2023-068

Polrob, W., & La-up, A. (2025). Nonlinear and lagged effects of climate variability on dengue incidence in an urban megacity: A distributed lag non-linear model (DLNM) based study in Bangkok, Thailand. BMC Public Health, 25, 4024.

R Core Team. (2025). R: A Language and Environment for Statistical Computing (Version 4.5.2) [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. Journal of the Royal Statistical Society Series B: Statistical Methodology, 71(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Seposo, X., Valenzuela, S., Apostol, G. L. C., Wangkay, K. A., Lao, P. E., & Enriquez, A. B. (2024). Projecting temperature-related dengue burden in the Philippines under various socioeconomic pathway scenarios. Frontiers in Public Health, 12. https://doi.org/10.3389/fpubh.2024.1420457

Siraj, A. S., Oidtman, R. J., Huber, J. H., Kraemer, M. U. G., Brady, O. J., Johansson, M. A., & Perkins, T. A. (2017). Temperature modulates dengue virus epidemic growth rates through its effects on reproduction numbers and generation intervals. PLOS Neglected Tropical Diseases, 11(7), e0005797. https://doi.org/10.1371/journal.pntd.0005797

Tewari, P., Ma, P., Gan, G., Janhavi, A., Choo, E. L. W., Koo, J. R., Dickens, B. L., & Lim, J. T. (2023). Non-linear associations between meteorological factors, ambient air pollutants and major mosquito-borne diseases in Thailand. PLOS Neglected Tropical Diseases, 17(12), e0011763. https://doi.org/10.1371/journal.pntd.0011763

The Lancet. (2024). Dengue: The threat to health now and in the future [Editorial]. The Lancet, 404(10450), 311–311. https://doi.org/10.1016/s0140-6736(24)01542-3

Tuan, D. A. (2024). Leveraging climate data for dengue forecasting in Ba Ria Vung Tau Province, Vietnam: An advanced machine learning approach. Tropical Medicine and Infectious Disease, 9(10), 250. https://doi.org/10.3390/tropicalmed9100250

Van Niekerk, J., Bakka, H., Rue, H., & Schenk, O. (2021). New frontiers in Bayesian modeling using the INLA package in R. Journal of Statistical Software, 100(2). https://doi.org/10.18637/jss.v100.i02

World Health Organization. (2025, December 26). Dengue: Global situation, surveillance and progress – 2024 update. https://www.who.int/publications/i/item/who-wer10052-665-678

How to cite this article:

Milla, N. E., Jr. (2026). Nonlinear and delayed effects of rainfall and temperature on dengue incidence in Eastern Visayas, Philippines: A Bayesian distributed lag nonlinear model approach. ***Recoletos Multidisciplinary Research Journal, 14***(2), 39-49. https://doi.org/10.32871/rmrj2614.02.04