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Bayesian modelling of dengue incidence with climatic drivers: comparing fixed-effects, nonlinear and dynamic approaches

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Abstract

Climatic variability plays a critical role in shaping dengue transmission dynamics, yet empirical findings remain inconsistent across studies. Divergent conclusions regarding the associations of temperature, relative humidity, wind speed, air pressure, precipitation, number of rainy days, and sunshine duration with dengue incidence often stem from unmodelled interactions and methodological limitations. To address these challenges, this study applies a Bayesian modelling framework to examine the associations between climatic drivers and dengue incidence in Bandung City, Indonesia, using monthly data from 2016 to 2024. We compared fixed-effects, nonlinear and dynamic modelling approaches to evaluate both the direction and magnitude of these associations while addressing overdispersion and potential multicollinearity among predictors. Our findings highlight temperature and relative humidity as the primary climatic variables associated with temporal variations in dengue incidence, with effects manifesting most strongly at a two-month lag. These results underscore the importance of adopting robust Bayesian modeling frameworks to support early warning systems and inform evidence-based public health interventions for dengue control.

Key words: Dengue incidence; climatic factors; Bayesian INLA; fixed-effects model; nonlinear modeling; dynamic modeling; Indonesia

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Introduction

Dengue fever is a mosquito-borne infectious disease that poses a significant global health threat, particularly in tropical and subtropical regions. According to the World Health Organization (WHO) estimates, approximately 390 million cases occur annually, with the highest burden reported in Asia (WHO, 2024; Jaya *et al.*, 2025). Transmission occurs through the bite of *Aedes aegypti* mosquitoes previously infected with the dengue virus (Roslan *et al.*, 2022). Despite ongoing research, no fully effective vaccine has been developed, and dengue incidence remains high worldwide, particularly in Asia, including Indonesia (Jaya and Folmer, 2020).

The risk factors associated with dengue incidence are diverse, encompassing population density, human mobility and environmental factors, including meteorological variables, such as temperature, precipitation and relative humidity (WHO, 2024; Amelinda *et al.*, 2022).. Among these, climatic variables – particularly temperature and precipitation – have received considerable research attention due to their complex and, in some contexts, nonlinear relationships with dengue transmission (Colón-González *et al.*, 2011; Campbell *et al.*, 2013; Morin *et al.*, 2013). Unlike population density and mobility, which consistently predict increased risk, the impact of weather conditions varies considerably across studies. Research conducted in tropical and subtropical regions of Southeast Asia has frequently reported a positive association between rainfall and dengue incidence, as increased precipitation creates favorable conditions for *Aedes* mosquito breeding (*e.g.*, Wang *et al.*, 2024). In contrast, studies from parts of Latin America, such as Paraguay, have documented negative associations, suggesting that excessive rainfall may disrupt larval habitats or reduce mosquito survival (Gómez *et al.*, 2022). These contrasting findings indicate that the effect of precipitation on dengue transmission is likely context dependent, varying with regional climatic conditions and local environmental characteristics (Abdullah *et al.*, 2022).

To better understand these dynamics, numerous modelling approaches have been applied to quantify the association between climate and dengue incidence. These include linear regression models (Colón-González *et al.*, 2011), time-series models such as Seasonal Autoregressive Integrated Moving Average models with exogenous regressors (SARIMAX) (Gharbi *et al.*, 2011; Karasinghe *et al.*, 2024), Poisson regression (Earnest *et al.*, 2012), Bayesian inference (Hu *et al.*, 2011; Jaya and Folmer, 2020; Al-Manji *et al.*, 2025), nonlinear frameworks (Descloux *et al.*, 2012; Kirk *et al.*, 2024), and dynamic models (Martínez-Bello *et al.*, 2017). Despite this methodological diversity, most studies have emphasized predictive accuracy over causal inference (Azhar *et al.*, 2017; Silva *et al.*, 2025; Lu *et al.*, 2025; Martheswaran *et al.*, 2022). Although predictive models are valuable for early warning systems, they often fail to uncover the causal mechanisms linking climate and dengue transmission. For policymakers, however, identifying these causal pathways is essential for designing effective control strategies. This challenge is particularly salient because climatic conditions cannot be directly controlled; instead, interventions must be strategically adapted to prevailing environmental dynamics.

A further challenge in predictive modeling lies in omitted variable bias, where unobserved confounders influence dengue transmission but are excluded from models due to data limitations. In panel data settings, fixed-effects models can mitigate this bias by incorporating unit-specific effects via dummy variables, producing a varying-intercept model estimated through the Least Squares Dummy Variable (LSDV) approach. For time-series data, time-varying coefficient models allow intercepts to evolve over time through a combination of fixed and random effects, often supplemented with lagged predictors (Ahmad *et al.*, 2021). In epidemiology, such frameworks are closely related to Generalized Additive Models (GAMs), which capture both nonlinear meteorological effects and their distributed lag structure (Yu *et al.*, 2025).

Given these complexities, we evaluated fixed-effect, nonlinear and dynamic models within a Bayesian framework. The Bayesian approach is particularly well-suited to this problem, as it accommodates complex model structures, accounts for multicollinearity among climatic predictors, and provides robust inference (Blangiardo and Cameletti, 2015). Count data are commonly modelled using Poisson regression; however, this approach relies on the equidispersion assumption, where the mean equals the variance. When overdispersion is present – *i.e.* when the variance exceeds the mean – the Negative Binomial regression provides a more appropriate alternative by explicitly allowing for extra-Poisson variability (Blangiardo and Cameletti, 2015).

This study focuses on Bandung City, West Java, Indonesia – a region with one of the highest annual dengue burdens nationwide. In 2024, Bandung City reported 7,680 cases, corresponding to an incidence rate of 296 per 100,000 population. The objective of this study is to identify the climatic variables most strongly associated with temporal variations in dengue incidence in Bandung City. The results are intended to inform the development of effective early warning systems and guide evidence-based public health interventions tailored to local climatic dynamics.

Materials and Methods

Study area

This study was conducted in Bandung City, West Java Province, Indonesia (Figure 1). Bandung City is one of the most densely populated cities in West Java, with a population density of 16,326 persons per km² and a total population of 2,506,203. The city is located at an elevation of approximately 700 meters above the mean sea level. Bandung covers a total area of 167.31 km², comprising 30 districts and 151 sub-districts. The average annual temperature is 24.25°C, with a maximum temperature of 36°C recorded in October and a minimum temperature of 15.4°C recorded in May. Rainfall occurs throughout the year with varying intensity across months, peaking in December at 365 mm and reaching its lowest level in September at only 18 mm (Bandung City, 2025).

Data

The data employed in this study comprised monthly records of dengue cases, population size, temperature (°C), relative humidity (%), wind speed (knots), air pressure (mb), precipitation (mm), number of rainy days, and sunshine duration. The study period spanned January 2016 to December 2024. Climatic variables were obtained from a single official meteorological monitoring station in Bandung City and were recorded at a monthly temporal resolution. Population data were sourced from the Bandung City in publications for the years 2017-2025 (Bandung City, 2017-2025). Dengue case data were sourced from the Bandung City Health Office and represent aggregated counts of dengue cases reported weekly by local hospitals and healthcare facilities to the municipal surveillance system, which were subsequently aggregated to the monthly level for analysis. The data used in this study correspond to officially recorded dengue cases compiled by the Health Office and are routinely used for epidemiological surveillance and public health reporting in Bandung City. All data were anonymized and aggregated at the city level; therefore, ethical approval was not required. No missing observations were identified in the final compiled monthly dataset.

Bayesian modelling for dengue incidence

To model the influence of the climatic variableson the dengue inci-

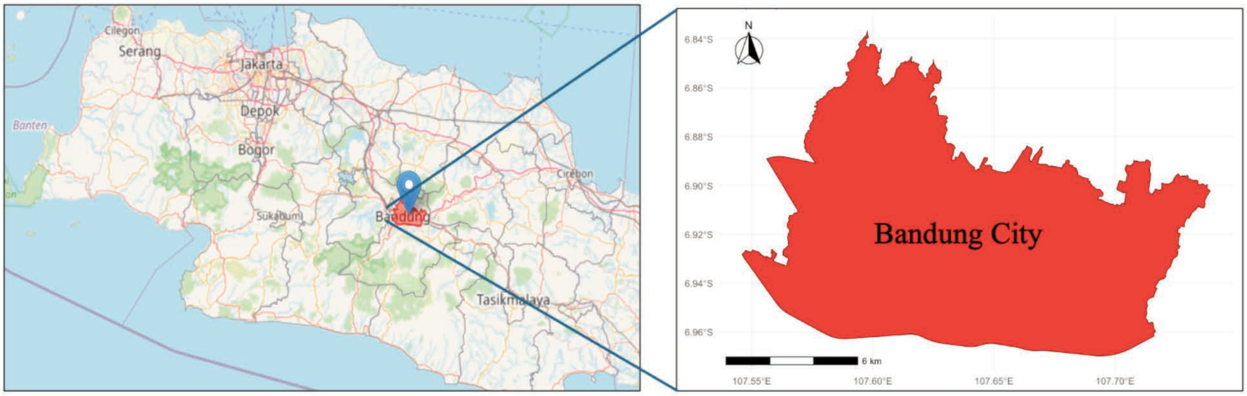

Figure 1. Map of Bandung City and its geographical position within West Java Province, Indonesia.

dence rate, we employed count regression models assuming either a Poisson or a negative binomial distribution. Both distributions were considered to identify the most appropriate model for the data, particularly to account for potential overdispersion commonly observed in infectious disease count data. The general Poisson regression model can be specified as follows:

$$y_t \mid \mu_t \sim \text{Poisson}\,(\mu_t) \qquad \text{(Eq. 1)}$$

with the mean (μ_t) structure:

$$\log(\mu_t) = \exp\left(\beta_0 + \sum_{j=1}^{J} \beta_j X_{jt} + \sum_{k=J+1}^{K} f_k\,(X_{kt}) + \sum_{l=K+1}^{L} \beta_l\,(t) X_{lt} + \delta_t + log(Population_t)\right) \qquad \text{(Eq. 2)}$$

here β_0 denotes the intercept; β_j fixed-effect coefficients for covariates X_{jt}; f_k (X_{kt})captures potential nonlinear effects of selected covariates; β_l (t) time-varying (dynamic) effects of covariates X_{lt}; and δ_t structured temporal effects. In principle, fixed, nonlinear and dynamic effects can coexist within a single model. However, to ensure model parsimony, reduce complexity and avoid potential identifiability and overfitting issues given the limited time-series length, we considered these components separately through a set of alternative model specifications As this strategy allowed us to assess the incremental contribution of each effect type and to identify the most appropriate model structure for the data.

Fixed effect model

In the fixed effect model, the regression coefficients are constant over time. The fixed effect model is specified as follows:

$$\log(\mu_t) = \beta_0 + \sum_{j=1}^{J} \beta_j X_{jt} + log(Population_t) + \delta_t \qquad \text{(Eq. 3)}$$

Nonlinear effect model

For the nonlinear model, it is assumed that there exists a non-linear relationship between log(μ_t) and the predictor X_{jt}

$$\log(\mu_t) = \beta_0 + \sum_{j=1}^{J} f_k\,(X_{jt}) + log(Population_t) \qquad \text{(Eq. 4)}$$

Dynamic effect model

For the dynamic effect, it is assumed that the effect of X_{jt} varies over time, which is commonly referred to as a time-varying coefficient model.

$$\log(\mu_t) = \beta_0 + \sum_{j=1}^{J} \beta_j\,(t) X_{jt} + log(Population_t), \qquad \text{(Eq. 5)}$$

Bayesian INLA

To estimate the Poisson and negative binomial regression models, we employed the Integrated Nested Laplace Approximation (INLA) framework. INLA provides a deterministic alternative to the traditional Markov Chain Monte Carlo (MCMC) approach for Bayesian inference and is particularly efficient for Latent Gaussian Models (LGMs), such as generalized linear models with fixed, nonlinear, and temporal components. Unlike MCMC, which relies on iterative sampling, INLA approximates the posterior distribution of model parameters through a sequence of deterministic approximations, making it computationally faster and highly accurate for complex hierarchical models (Blangiardo & Cameletti, 2015; Jaya & Folmer, 2020).

The INLA procedure involves three main steps. First, the marginal posterior of the hyperparameters (ψ) is approximated, where INLA employs a Laplace approximation to $\pi(\psi|y)$; next, conditional on selected values of the hyperparameters, accurate approximations to the marginal posterior distribution of each latent variable θ_t=(β_0, β_1, … , β_K, β_{1t}, … , β_{Kt})', $\pi(\theta_t|y,\psi)$, are derived. Finally, the marginal posterior distributions of the latent variables, $\pi(\theta_t \mid y)$, are obtained by numerically integrating over the approximated hyperparameter distribution.

The faster yield of reliable results makes it particularly efficient for epidemiological applications, where complex structures and multiple random effects must often be accounted for. In this study, two prior specifications – Random Walk of order 1 (RW1) and Random Walk of order 2 (RW2) – were considered to model nonlinear effects of selected covariates within the Bayesian INLA framework. RW priors are commonly used for flexible smoothing of nonlinear covariate effects and gradual temporal evolution. For the dynamic model, covariates retained from the fixed-effects specification were allowed to have time-varying regression coefficients (β), which were modelled using a first-order random walk. Seasonal temporal dependence was captured using autoregressive structures, while RW priors were used to represent smooth changes in covariate effects over time. Model adequacy was assessed through Bayesian model comparison, with emphasis on parsimony due to the limited temporal sample size. Prior sensitivity was evaluated by comparing RW1 and RW2 specifications for nonlinear covariate effects, and model fit under each prior was examined to assess robustness to alternative smoothing assumptions. Both Poisson and negative binomial distributions were considered across all model specifications to account for potential over-dispersion in the count data. The complete specification of priors and hyperpriors is provided in *Supplementary materials Table 1.*

Results

Exploratory data analysis

The total number of reported dengue cases during the study period from 2016 to 2024 was 34,190. The average monthly case count was 317, with a median of 245, ranging from 60 to 1,225 cases. Al most every year, Bandung City experienced either a dengue outbreak or a high-risk transmission period. In this study, an outbreak or high-risk period was defined as a year, in which the dengue Incidence Rate (IR) exceeded 100 cases per 100,000 population, a threshold commonly used in epidemiological surveillance to indicate elevated dengue transmission. Based on this criterion, IRs exceeded 100 cases per 100,000 population in 7 of the 9 years during the study period, with particularly high values observed in 2016, 2019, 2020, 2021, 2022 and 2024. In contrast, relatively lower incidence rates were observed in 2017 and 2023 (Figure 2). The partial autocorrelation function (PACF) of the dengue case time series (Figure 3) suggests the presence of autoregressive dependence at short lags, potentially corresponding to an

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AR (1)-AR (3) process. These patterns are indicative of seasonal and short-term temporal dependence in dengue incidence.

The descriptive statistics of the climatic variables are shown in *Supplementary materials Table 2,* while Figure 4 illustrates the temporal patterns and cross-correlations between climate variables and dengue cases. Temperature showed an increasing trend from 2018 to around 2021 with consistent seasonal fluctuations. Cross-correlation analysis indicated that temperature significantly affects dengue incidence with a 1-4 month lag, peaking at 2–3 months. This suggests that higher temperatures are followed by increased dengue cases, making temperature a potential early warning indicator. Relative humidity displayed strong seasonal variation without a clear long-term trend. Cross-correlation results revealed a significant negative correlation at lags of 2-4 months, indicating that a decrease in humidity often precedes an increase in dengue cases. Thus, humidity may serve as a negative but useful predictor. Air pressure exhibited inter-seasonal variability without a consistent trend. A significant positive correlation with dengue cases was observed at lags 1-5 months, peaking at lag 3. Although weaker than temperature, air pressure can still contribute as a climate-based predictor for dengue risk. Rainfall presented highly fluctuating patterns with intense peaks but no annual consistency. It showed a significant negative correlation with dengue at lags 1-6 months, especially at lags 3-5. This suggests that heavy rainfall might reduce dengue transmission, potentially due to disruption of mosquito breeding habitats. Rainy days followed a seasonal pattern with no long-term trend. A strong negative correlation was found at lags 2-4 months (strongest at lag 3), implying that increased rainy days reduce future dengue incidence. Solar radiation and sunshine duration both showed consistent seasonal cycles. Cross-correlation indicated a significant negative relationship with dengue cases at lags 1-4 months, especially around lag 2. Decreased sunlight may lead to higher dengue risk by favoring mosquito survival. In general, significant correlations were

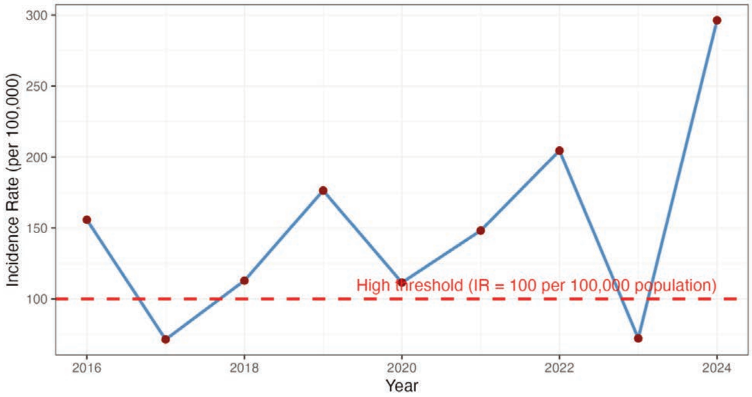

Figure 2. Incidence rate of dengue disease per 100,000 population (2016-2024).

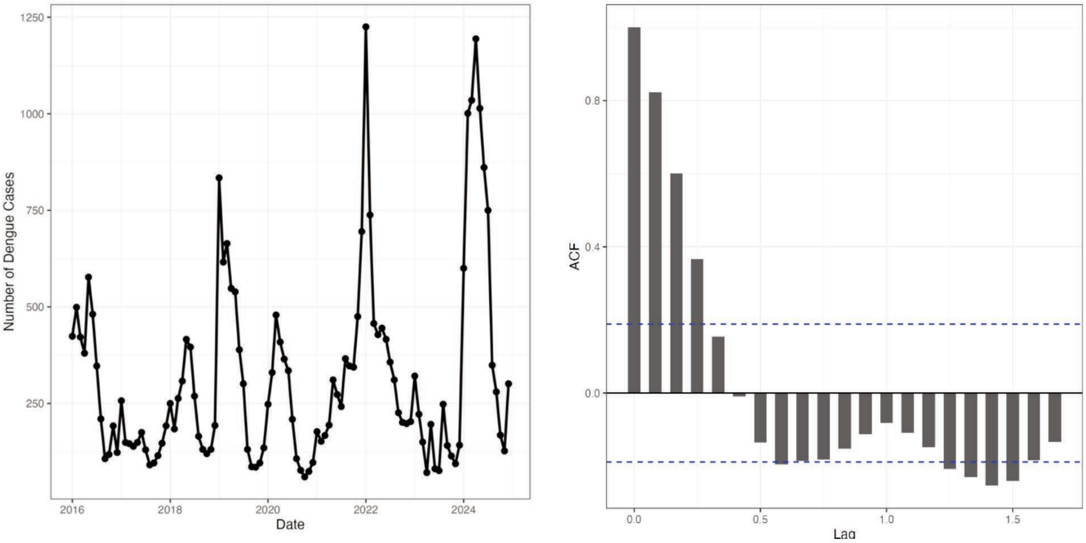

Figure 3. Monthly temporal trend and ACF of number of cases. ACF, autocorrelation fuction.

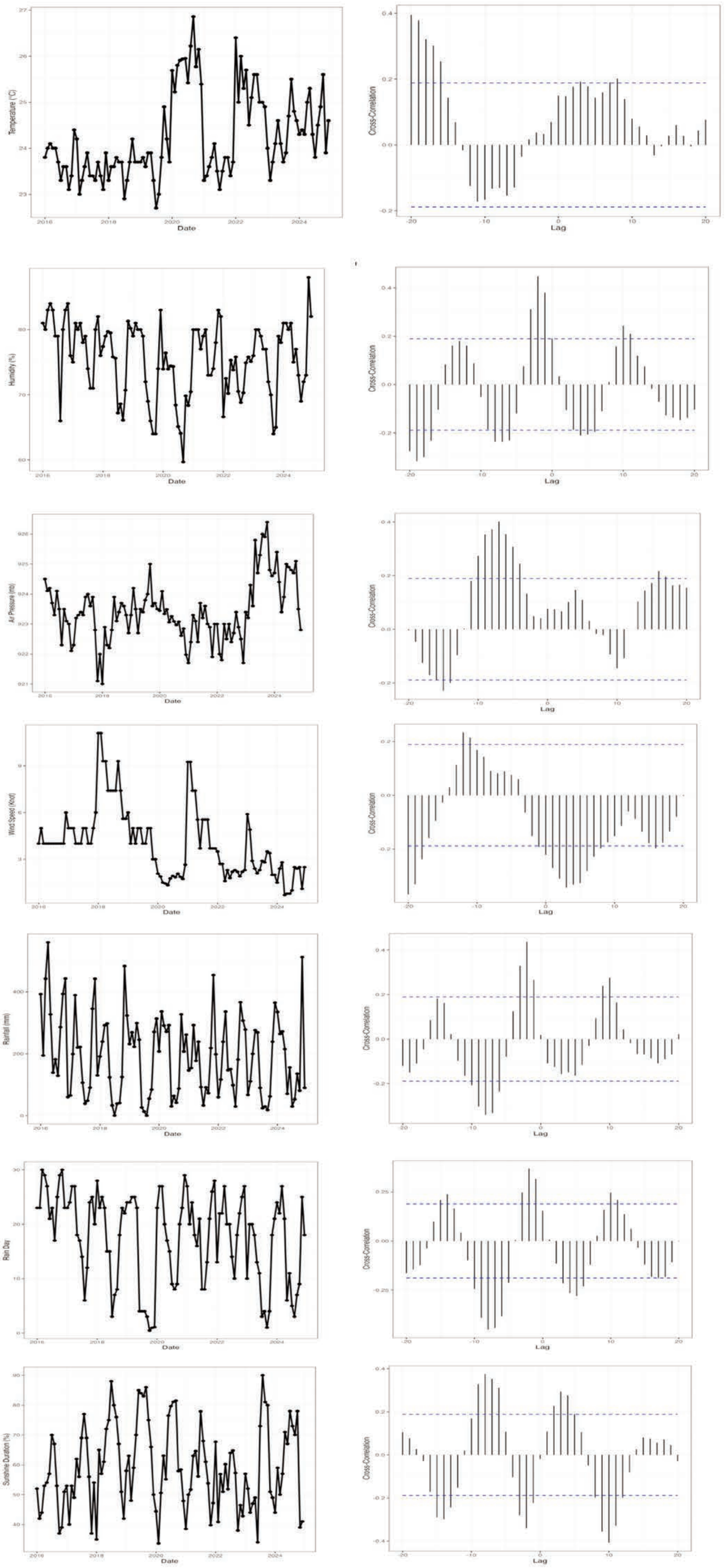

Figure 4. Temporal patterns of climatic variables and their cross-correlations with dengue incidence.

observed between lags 0 and 3; therefore, only these lags were considered in the subsequent analysis. Figure 5 shows, the correlation matrix plot reveals heterogeneous relationships among the climatic variables. Positive correlations (red areas) indicate groups of variables that tend to increase simultaneously, such as temperature and relative humidity at specific lags. In contrast, negative correlations (blue areas) highlight opposing patterns, for instance, between precipitation and sunshine duration. The varying strengths and directions of these associations suggest that the effects of climatic drivers on dengue incidence are not uniform across time lags. Moreover, the presence of strong correlations among certain predictors indicates potential multicollinearity, which must be carefully addressed in subsequent modelling.

Model selection

Model selection is a critical first step in assessing the influence of weather variables on dengue incidence rates. In this study, we compared three alternative approaches: a fixed-effects model with lagged independent variables, a nonlinear model and a dynamic model. At the initial stage, variable selection was conducted using all independent variables with a maximum lag of three periods. The optimal set of predictors was identified through a backward selection procedure based on the Watanabe-Akaike Information Criterion (WAIC). The nonlinear model was subsequently applied to determine whether the selected variables exhibited linear or nonlinear relationships with dengue incidence. Finally, the same set of variables was incorporated into a dynamic modelling framework to capture temporal dependence and lagged associations between climatic factors and dengue incidence. Variable selection from the fixed-effects model, based on predictive performance and model fit, is summarized in *Supplementary materials Table 3.*

The variable selection process using the backward selection method was completed in 17 steps, with the 17th model (F-17) yielding the smallest WAIC value of 1324.71 under the negative binomial distribution. The next stage involved modeling the selected independent variables using a nonlinear approach. We assumed that the variables retained in the fixed effect model represent those most relevant to the dengue incidence rate and should therefore be considered in subsequent model specifications, namely the nonlinear and dynamic models.

Subsequently, the independent variables selected from the fixed-effects model were examined using a nonlinear specification. *Supplementary materials Table 4* summarizes the results for the nonlinear model. The best-fitting specification suggests that dengue incidence is associated with relative humidity, with temperature exhibiting a nonlinear relationship, while air pressure, sunshine duration and wind speed enter the model linearly. For the negative binomial likelihood, the nonlinear model yielded a WAIC value of 1382.997. Although this value is higher than that of the corresponding fixed-effects model, the comparison is interpreted cautiously, as the two specifications differ in functional form and complexity. The nonlinear model was therefore treated as an exploratory step to assess potential departures from linearity rather than as a directly competing alternative to the fixed-effects specification.

Subsequently, a dynamic model was developed using the variables selected from the fixed effect model. The results (seen in *Supplementary materials Table 5* indicated that the best-performing specification was model D5, which achieved the lowest WAIC under the Poisson distribution. This model identified air pressure as the only variable that dynamically explained the dengue incidence rate (WAIC = 944.44).

In *Supplementary materials Table 6*, three modeling approaches are compared: i) a fixed effect model with selected lags, ii) a nonlinear model, in which temperature and relative humidity were modelled with smooth functions while air pressure, sunshine duration, and wind speed were modelled linearly, and iii) a dynamic time-varying coefficient model focusing on air pressure. The dynamic specification yielded the lowest WAIC; however, this may partly reflect its higher effective complexity. Models with time-varying coefficients are more prone to overfitting and are less straightforward to interpret.

Before selecting the dynamic model as the preferred specification, several criteria were carefully evaluated: i) model calibration, assessed through probability integral transformation (PIT) values close to uniformity and the absence of extreme −log(CPO) values; ii) residual diagnostics and autocorrelation functional (ACF) behavior; iii) model fit as indicated by WAIC; iv) predictive performance under blocked time-series cross-validation; and v) robustness to more restrictive RW specifications and potential identifiability issues between α(t) and $\beta_{AP}(t)$. For the nonlinear effects, RW1 was selected over RW2 based on a lower WAIC value (1,375 *vs* 1,376).

As seen in *Supplementary materials Table 7* and Figure 6, the dynamic model appears to be the best-performing specification in terms of model fit, as it yielded the lowest WAIC, Deviance Information Criterion (DIC), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) values, as well as the highest R^2. However, the values are excessively high – particularly the R^2 equal to 1 – indicating overfitting. This concern is further supported by the PIT results, where the *p*-value equals zero, suggesting that the PIT distribution deviates substantially from the uniform

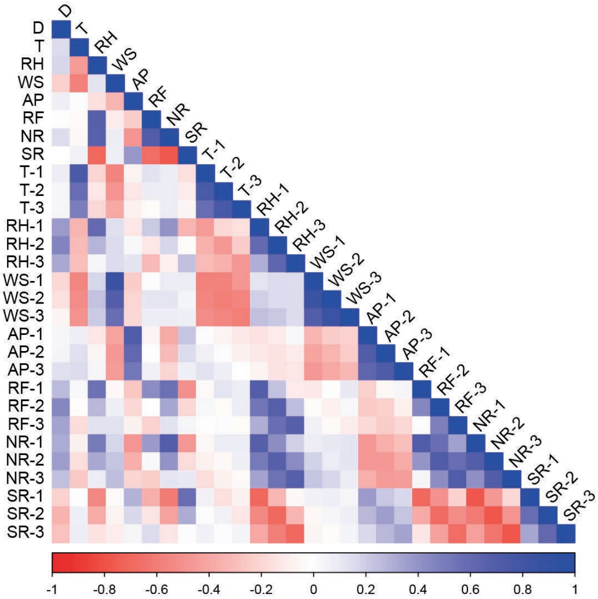

Figure 5. Correlation matrix plot of monthly dengue cases with meteorological variables at lag 0, lag 1, lag 2 and lag 3. T, Temperature; RH, Relative Humidity; AP, Air Pressure; WS, Wind Speed; RF, Precipitation (Rainfall Amount); NR, Number of Rainfall Events; SR, Sunshine Duration. The subscripts _0, _1, _2, and _3 indicate temporal lags.

distribution. This deviation is also evident in Figure 1, where the PIT pattern for the dynamic model clearly is far from uniform. In contrast, the fixed effect model emerges as the most appropriate candidate, showing better calibration than the nonlinear model, particularly in terms of its PIT behavior. Accordingly, the fixed model was selected for subsequent analyses. Nonetheless, this model still exhibits some issues regarding model fit, which could be improved through the selection of significant variables and by incorporating linear trend or seasonal effects.

Improvement of the fixed model

Variable selection in the fixed-effects model was conducted as an exploratory screening step based on predictive performance measured by WAIC. This procedure was used to identify covariates with the strongest empirical association with dengue incidence, rather than to establish statistical significance in a causal sense. As a result, some variables retained in the model have credible intervals that include zero, reflecting uncertainty in their estimated effects. *Supplementary materials Table 8* presents the posterior summaries of the fixed-effects model parameters.

Based on the 95% credible intervals [$q(0.025)$, $q(0.975)$], the variables SR_0, SR_1, T_2, WS_2, AP_2, WS_3, and SR_3 (see the table) were initially identified as not statistically significant because their credible intervals included zero. A backward elimination procedure was then applied, in which non-significant variables were removed sequentially, starting with those showing the weakest evidence of association (*i.e.* credible intervals most centred around zero). Due to correlations among covariates, the removal of one variable affected the posterior estimates and uncertainty of the remaining ones. After each removal step, the model was re-estimated and the statistical relevance of the remaining covariates reassessed. This iterative procedure continued until all retained variables exhibited credible intervals that excluded zero. Following this process, temperature at lag 0 (T_0) and relative humidity at lag 2 (RH_2) were identified as statistically significant. The final model was defined as:

$$\log(\hat{\mu}_t) = -9.099 + 0.212\,T_t + 0.487\,RH_{t-2} + \log(\text{population}_t).$$

Although this model included two statistically significant variables, the evaluation results (Figure 7) indicate relatively weak predictive performance, with an R² value of only 0.376, and the residual normality check still showing deviations. Therefore, potential improvements may involve incorporating random trend or seasonal effects. However, the addition of random effect components should be constrained to ensure that the fixed effects remain statistically significant.

Supplementary materials Table 9 presents a comparison of

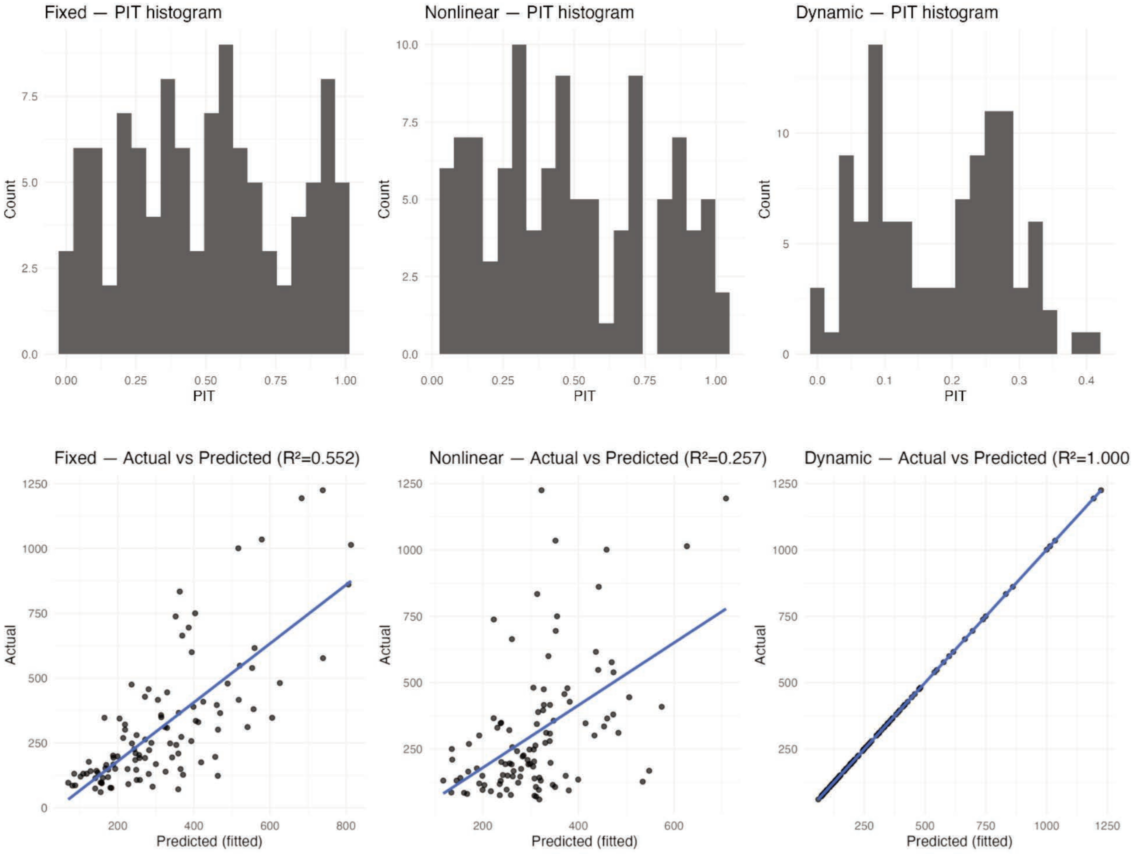

Figure 6. PIT and R² for model evaluation. PIT, probability integral transformation.

three models: M-1, which incorporates both trend and seasonal components; M-2, which includes only the trend component; and M-3, which includes only the seasonal component. The results indicate that, overall, adding a trend component leads to lower WAIC values. However, as shown in *Supplementary materials, Table 10*, the inclusion of the trend component renders the fixed effect of temperature statistically non-significant. This outcome is undesirable from an inferential perspective, as temperature represents a key climatic covariate of substantive interest. Consequently, Model M-3 – a fixed-effects model augmented with a seasonal component – was selected, as it effectively captures residual temporal patterns not explained by temperature and relative humidity at lag two. As shown in Figure 8, M-3 demonstrates improved performance compared to the corresponding fixed-effects model without seasonal adjustment, with the R^2 increasing from 0.376 to 0.414. In addition, the residuals more closely approximate a normal distribution, indicating improved model adequacy. Accordingly, the best-performing model in this study was selected based on a combination of statistical adequacy, parsimony and inferential validity.

Model interpretation

After identifying Model M-3 as the best-fitting specification – with a fixed effect of temperature at lag 0, a fixed effect of relative humidity at lag 2, and the addition of a seasonal component with a 12-month period – the next step was to interpret the model parameters. Prior to interpretation, the regression coefficients were rescaled to the original units of each variable, as all variables had previously been standardized for computational purposes. The rescaled regression parameters are presented in *Supplementary materials Table 11*. Based on *Supplementary materials Table 9*, the lag-0 temperature Incidence Rate Ratio (IRR) of 1.415 indicates that 1°C increase is associated with 41.5% increase in the incidence rate, holding other variables constant. The lag-2 relative humidity IRR of 1.068 implies that a one-percentage-point increase in relative humidity two months earlier is associated with a 6.8% increase in the incidence rate. The 12-month seasonal component (Figure 9) exhibits a clear annual pattern, with a peak around March and a trough around August: the seasonal contribution is generally positive from January to July, negative from August to October, and positive again from November to December.

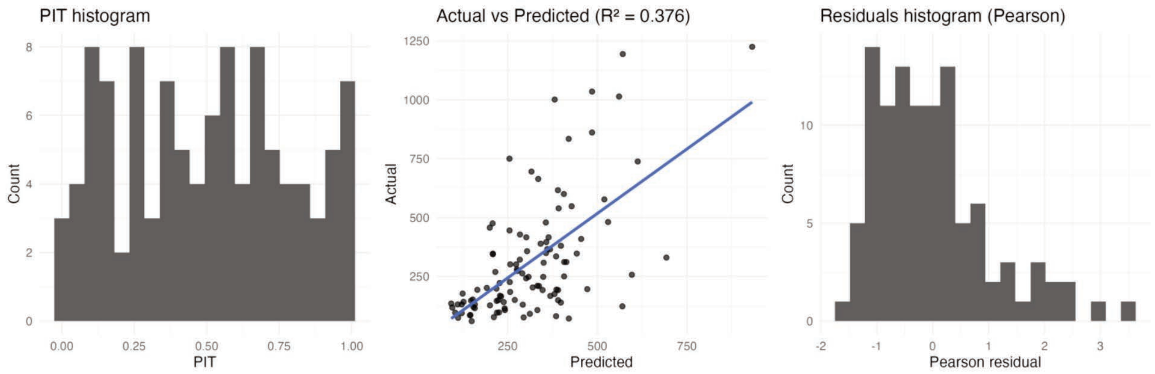

Figure 7. Model evaluation of log($\hat{u}_t$)= -9.099+0.212T_t+0.487 RH_{t-2}+log(population$_t$).

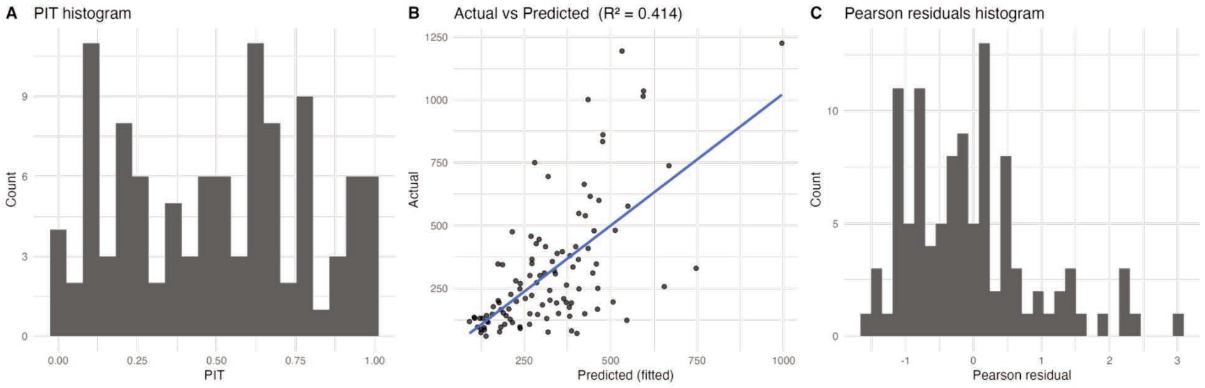

Figure 8. Evaluation of Model M-3.

Discussion

This study examineed the relationship between dengue incidence and climatic factors in Bandung City, Indonesia over the period January 2016 to December 2024. Although numerous studies have analyzed the association between dengue transmission and climate variables (Monintjaa *et al.*, 2021; Gómez *et al.*, 2022; Figueredo *et al.*, 2023; Wang *et al.*, 2024; Majeed *et al.*, 2025), empirical evidence specific to Bandung City remains scarce. Understanding how climatic conditions influence dengue incidence in this setting is critical for advancing knowledge of vector–climate interactions and for informing local public health interventions. The findings of this study are expected to provide a scientific basis for the Bandung City Government in developing early warning system strategies aimed at reducing the spread and burden of dengue cases.

Using a Bayesian framework to compare multiple model specifications, our analysis identified the fixed effects model with an added seasonal component as the best-performing specification. Within this model, two climatic variables were found to significantly influence dengue incidence in Bandung City: temperature at lag 0 and relative humidity at lag 2. These findings align with previous studies that have consistently highlighted temperature and relative humidity as key determinants of dengue transmission dynamics (Gómez *et al.*, 2022; Figueredo *et al.*, 2023; Wang *et al.*, 2024). Overall, the effect of temperature appears relatively consistent across study locations, with higher temperatures generally associated with increased dengue incidence (Gómez *et al.*, 2022; Wang *et al.*, 2024). Our results similarly indicate a positive association between temperature and dengue incidence. Warmer temperatures accelerate the development and hatching of *Aedes aegypti*, the primary vector of dengue transmission, and increase mosquito feeding activity, providing a biologically plausible mechanism for this association. Although the temperature–dengue relationship is inherently nonlinear, temperature was modeled linearly in this study as a parsimonious local approximation within the observed range in Bandung City, while nonlinear temporal dynamics were captured through the seasonal component (Figure 9).

In contrast, the effects of relative humidity vary across geographic settings. For example, Gómez *et al.* (2022) reported a negative association between relative humidity and dengue incidence in Asuncion, Paraguay, whereas Wang *et al.* (2024) found a positive relationship in South and Southeast Asian countries, particularly under warm temperature conditions. The results of Wang *et al.* (2024) are consistent with our findings, which also indicate a positive effect of relative humidity in in Southeast Asia, in this case Bandung City, Indonesia. Our conclusions are further supported by Monintjaa *et al.* (2021), who also observed a positive relationship between relative humidity and dengue incidence.

The divergent findings across studies examining the influence of climatic factors on dengue incidence often arise from differences in the choice of analytical model. Predictive models typically prioritize minimizing error metrics – such as Mean Squared Error (MSE) and MAE – and maximizing R² to achieve greater forecasting accuracy. However, a predictive framework is not appropriate for inferential (causal) modelling, where the emphasis lies in understanding how independent variables influence the dependent outcome rather than in maximizing predictive performance. In causal modelling, careful attention must be paid to potential confounders. A recommended strategy is to select candidate predictors based on theoretical justification and prior evidence. If a theoretically relevant variable is found to be statistically non-significant, it may be excluded from the model – provided that its omission does not materially affect the estimated effects of the remaining variables. Model validity also depends on the assumption that residuals approximate white noise. In time-series analyses, this assumption can be supported by incorporating structured temporal random effects or trend and seasonal components. For a more detailed discussion of confounding issues, see Ramspek *et al.* (2021) and Jaya and Folmer (2024).

Study limitations

This study is subject to several limitations. First, data availability constrained the analysis to monthly observations covering a nine-year period from 2016 to 2024. The use of monthly data may smooth short-term fluctuations in dengue transmission dynamics, and weekly data would be more appropriate given the life cycle of *Aedes aegypti*. Nevertheless, the modelling strategy deliberately avoided long lag structures, with a maximum lag of two months, consistent with the biological development cycle of the dengue vector. Moreover, the Bayesian modelling framework employed allows for robust inference without requiring very large sample sizes. Dengue surveillance data may also be affected by reporting delays and potential underreporting, which could introduce measurement error in the observed incidence counts. Second, the analysis was conducted at the city level and does not fully capture spatiotemporal heterogeneity across districts. Bandung City consists of 30 districts with diverse characteristics, and the effects of cli-

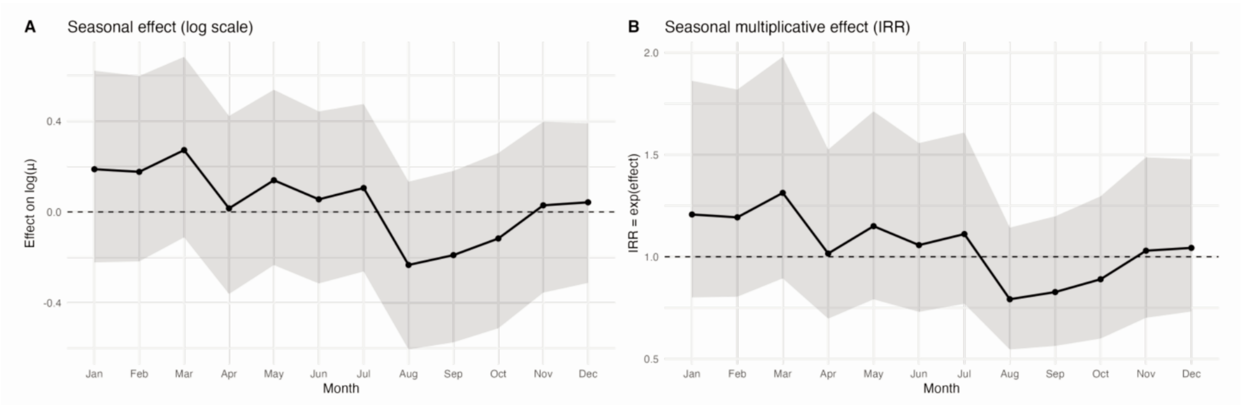

Figure 9. Seasonal effects.

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matic factors may vary spatially. However, climatic data were available from only a single monitoring station, which was considered sufficient given the relatively small geographic size of the study area. This spatial aggregation may limit the effective sample size for temporal inference. Future studies would benefit from district-level weather monitoring and the adoption of spatiotemporal modelling frameworks to better capture intra-urban variability in dengue transmission.

Conclusions

Our study, through the exploration of fixed-effects, nonlinear, and dynamic models, found that temperature at lag 0 and relative humidity at lag 2 were significantly associated with temporal variation in dengue incidence in Bandung City. Both variables exhibited a positive association with increases in monthly dengue cases across the modelling approaches considered. While these findings highlight the relevance of climatic factors in explaining dengue dynamics, they should be interpreted as associational evidence derived from observational data. To obtain more robust inference and to better capture the temporal dynamics of mosquito life cycles, future studies would benefit from data with higher temporal resolution, such as weekly dengue surveillance and meteorological records.

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Online supplementary materials

Table 1. Prior and hyperprior distributions for fixed effect, nonlinear and dynamic models.
Table 2. Descriptive statistics of climatic variables.
Table 3. Variable selection in the fixed effect model.
Table 4. Specification for the nonlinear effect model.
Table 5. Specification for the Dynamic Model.
Table 6. Summary of model selection results.
Table 7. Comparison of fixed, nonlinear, and dynamic effect models.
Table 8. Parameter estimates of the fixed effect model (F-17).
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Table 10. Parameter Estimates of M-1, M-2, and M-3.

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