The Influences of Climate Change and Social Vulnerability on Dengue Fever Incidence Rate in West Java Province 2019–2023

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Abstract. In Indonesia, dengue fever is a serious public health problem. The increase in dengue fever cases is influenced by climate change and social vulnerability factors. This study focuses on West Java Province in 2019–2023, aiming to describe the spatial-temporal pattern of dengue fever incidence and analyze the influence of climate factors and social vulnerability using a spatial-temporal model, namely Geographically Temporally Weighted Regression (GTWR). The exploration results show a high concentration of dengue fever incidence rates in 2019, while in 2023, the intensity of dengue fever incidence decreases. The GTWR model produces local parameters across various regions and time periods, indicating that in most regencies/cities, rainfall, population density, access to inadequate sanitation, health facility ratio, and education level have a positive effect on dengue fever incidence rates, while land surface temperature and the percentage of poor people have a negative effect. From the GTWR model results, areas with high levels of dengue fever vulnerability can be identified as priorities for dengue fever management interventions. Therefore, this study contributes to early warning research and dengue fever control program planning by considering the risk of dengue fever vulnerability in each region.
Keyword: Climate Change, Dengue Fever, GTWR, Social Vulnerability.

1. Introduction

Dengue hemorrhagic fever (DHF) is a disease transmitted through vectors (mosquitoes). The incidence of DHF has increased drastically worldwide in recent decades, with cases reported to the World Health Organization (WHO) increasing from 505,430 cases in 2000 to more than 6.5 million cases and more than 7,300 deaths due to DHF reported in 2023. Diseases transmitted by vectors in the form of mosquitoes are a major challenge of neglected tropical diseases in efforts to achieve Sustainable Development Goals 3.3 (SDGs 3.3): " By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases." An increase in new cases of dengue fever infections occurs annually, recorded in more than 100 dengue-endemic countries, including countries in Southeast Asia, Africa, the Americas, the Eastern Mediterranean, and the Western Pacific [1]. Countries in the Southeast Asian region contribute the most cases of dengue fever globally [2]. Global Strategy for Dengue Prevention and Control places Indonesia as the country with the second-highest number of dengue fever cases in the world [1].

The government's commitment has been outlined in the 2020–2024 National Medium-Term Development Plan (RPJMN), which emphasizes the prevention and control of dengue fever risk factors. In order to achieve zero dengue deaths by 2030, the 2020–2024 RPJMN has set a target indicator of 95% of regencies/cities with a dengue fever incidence rate of less than 10 per 100,000 population by 2024. Dengue fever transmission has the potential to trigger extraordinary events that cause community vulnerability and can lead to death. In the Roadmap Neglected Tropical Diseases (NTDs) 2021–2030, dengue fever is included in the target of 20 diseases and disease groups to be prevented and controlled. The target for dengue fever control is to reduce the death rate (Case Fatality Rate, CFR) from 0.50% in 2024 to 0% in 2030 [3]. By the end of 2023, cases of dengue fever occurred in 464 regencies/cities in 34 provinces in Indonesia. The distribution of dengue fever deaths was concentrated in three provinces on the island of Java, namely West Java, Central Java, and East Java, which contributed 31% of the total 114,720 cases in Indonesia. The three provinces with the highest dengue fever incidence rates during the 2019–2023 period were West Java, East Java, and Central Java. Among the three, West Java had the highest average dengue fever incidence rate during that period, at 52.07 cases per 100,000 population per year, followed by East Java (28.13) and Central Java (21.96). West Java Province consistently had a higher dengue fever incidence rate than East Java and Central Java throughout 2019 to 2023. Although the dengue fever incidence rate in West Java decreased in 2023, it remained far above the RPJMN target of less than 10 cases per 100,000 population.

West Java Province is one of the most densely populated regions in Indonesia, with a population of approximately 50 million. West Java's proximity to Jakarta makes it a hub of economic activity and high population mobility. This contributes to high vulnerability to infectious diseases such as dengue fever, primarily due to the spatial heterogeneity in population distribution and healthcare infrastructure [4]. Dengue fever transmission in highly densely populated areas, with a population density of ≥1,000 people/km^2 has the highest rate of dengue exposure [5]. In addition, rapid urbanization due to economic growth in the central, northwest, and northeastern regions of West Java increases the opportunity for expansion of the Aedes aegypti vector habitat, thereby accelerating the spread of the virus. The high incidence of dengue fever is caused by various social and environmental factors, such as population density and mobility [2]. Climate change is known to be a driver of increased vectors and dengue transmission [6]. Climate change can be seen in the increase in above-average temperatures each year and increased annual rainfall. Over the past 30 years, Java Island has experienced an increasing average temperature trend [7] and is projected to be one of the areas most affected by rising surface temperatures and changing rainfall patterns [8].

Dengue fever transmission by Aedes mosquitoes is higher in areas with high levels of vulnerability, such as areas with high levels of poverty, limited access to health care, and inadequate sanitation [9]. This indicates that the vulnerability of the population to infectious diseases is determined by the level of dengue fever as the exposure population to the condition [5]. This supports the existence and transmission vector, which relates to water and vulnerability to socio-cultural, economic which form sensitivity to the impact of Dengue Fever. Social vulnerability measurement (Social Vulnerability) functions to determine the level of community sensitivity to global change and the community's ability to respond and recover from the negative impacts caused by disasters due to climate change [10].

Climate change and social vulnerability have the potential to increase the risk of dengue fever transmission. Global climate change impacts the spread of vector-borne infectious diseases, such as accelerating the rate of reproduction, increasing the vector's ability to invade, and shortening the pathogen's incubation period [6]. Conversely, areas with high levels of social vulnerability have a higher risk of dengue virus transmission than areas with low levels of social vulnerability. Dengue transmission depends on the interaction between the host, the virus, the mosquito, and environmental factors. Given the limited flight range of mosquitoes (generally 512 meters or less), local dengue transmission is generally influenced by population density and movement, both on a broad scale (national or international) and a smaller scale (regional, regencies, community, or neighborhood) [11]. Furthermore, dengue cases tend to form clusters both in space and time, so spatial analysis is necessary to understand the factors supporting dengue transmission [12].

Extensive research on dengue fever has been conducted, including temporal, spatial, spatio-temporal modeling, and vulnerability mapping. Research and development of a temporal prediction model for dengue fever incidence used the Generalized Additive Models (GAMs) [13]. Spatial modeling has also been carried out based on the influence of environmental and social factors on the spatial distribution of dengue fever using the Geographically Weighted Regression (GWR) [14]. Meanwhile, modeling is Bayesian modeling has also been done by using a Bayesian hierarchical spatial model to model the spread of dengue fever [15]. Mapping of vulnerability to dengue fever was also studied using a multi-criteria decision analysis (MCDA) approach based on social and climate aspects [16]. However, previous studies have generally been limited to a single dimension (spatial/temporal only) and have not integrated vulnerability aspects into a spatial-temporal approach. However, changes in social and climate vulnerability phenomena also indicate that risks are non-static, meaning they change over time, and these changes must be considered, both in current vulnerability assessments and in developing corrective interventions (for existing risks) and prospective (for future risks) [9].

Most spatial-temporal modeling uses global modeling that assumes spatial-temporal effects are constant across regions. However, this assumption of stationarity over time and space is generally unrealistic because parameters tend to vary across regions [17]. Research proposed Geographically Weighted Regression (GWR) for coefficient variation analysis and testing the significance of spatial variation [18]. Spatial-temporal weighting matrix to combine spatial and temporal information to form a Geographically-Temporally Weighted Regression (GTWR) model [19]. GTWR model parameter estimation is performed locally for each location and time point, thus capturing the spatial-temporal heterogeneity of the influence of climate change and social vulnerability factors on dengue fever incidence rates. Therefore, this study contributes by applying the GTWR model to determine the influence of spatial and temporal heterogeneity on dengue fever incidence rates while identifying significant influences of climate change and social vulnerability factors. Furthermore, GTWR results are also expected to provide spatial-temporal information that can be useful for determining priority areas for dengue control interventions.

Based on problem identification, this research focuses on West Java Province in 2019–2023, with the following objectives:

1. Obtaining a general spatial and temporal overview of the incidence rate of dengue fever.
2. Analyzing the influence of climate change and social vulnerability on the incidence rate of dengue fever.

The data on dengue fever used in this study were obtained from reports from health facilities, such as hospitals and community health centers, collected through the official surveillance system of the Ministry of Health of the Republic of Indonesia. This data does not differentiate between the number of patients diagnosed with Dengue Fever, Dengue Hemorrhagic Fever, or Dengue Shock Syndrome. Reports from health facilities may be subject to reporting bias, particularly if there are undiagnosed or unreported cases, such as patients who do not access health services.

2. Research Method

The data for this study are secondary data obtained from the Public Health Office, Satellite Imagery, and the Central Statistics Agency (BPS). Moderate Resolution Imaging Spectroradiometer (MODIS) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) satellite imagery data were collected from 2019–2023 using Google Earth Engine (GEE) Code Editor as presented in Table 15. Meanwhile, official data statistics were obtained from BPS and the Public Health Office as displayed in Table 16.

Table 15. Research variables from satellite imagery data

Variable *(unit)*	Source Resolution		GEE Catalog Source
	Spatial	Temporarily	

Land surface temperature (°*C*)	1 km	8 days	MODIS_006_MOD11A2
Rainfall (*mm/year*)	~5 km	24 hours	UCSB-CHG_CHIRPS

Table 16. Research variables from official data statistics

Variable *(unit)*	Source
Dengue fever incidence rate (*cases/100,000 population*)	public health office
Percentage of poor population (*%*)	BPS
Population density (*people/km²*)	BPS
Percentage of households that do not have access to proper sanitation (*%*)	BPS
The ratio of health facilities (*number of primary health care center, integrated health post, and hospital/100,000 population*)	public health office
Percentage of female population aged 25 years and over with at least a high school education (*%*)	BPS

In order to obtain a general picture of the characteristics of the research variables, the answer was to use Exploratory Spatial-Temporal Data Analysis (ESTDA) is a descriptive analysis technique for data sets that encompasses both spatial and temporal aspects. In this study, ESTDA is presented using thematic maps to depict the research variables annually for each regency/city. Furthermore, boxplot visualization is used to observe the distribution and changes in data trends. Inferential analysis in this study was conducted to determine the influence of climate change factors and social vulnerability on the incidence rate of dengue fever using a spatial-temporal model: GTWR.

2.1. Geographically-Temporally Weighted Regression (GTWR)

Fotheringham et al. [13] used a weighting matrix to combine spatial and temporal information to form Geographically-Temporally Weighted Regression (GTWR). The matrix is constructed based on the spatial-temporal distance calculated from the coordinates (u_i, v_i, t_i) between the observation point $i$and all other observations.

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \quad (1)$$

with,

y_i : Dependent variable (dengue fever incidence rate) at location and time *i*

X_{ik} : Independent variables *k* at location and time *i*

$\beta_0(u_i, v_i, t_i)$: Coefficient intercept at the observation location (u_i, v_i) and time(t_i)

$\beta_k(u_i, v_i, t_i)$: Regression coefficient of independent variables on location (u_i, v_i) and time (t_i)

ε_i : observation error at the assumed location and time *i*, $\varepsilon_i \sim N(0, \sigma^2)$.

GTWR parameter estimation uses the Weighted Least Square (WLS). WLS estimation assumes that *the* error $\boldsymbol{\varepsilon}$ are not correlated with each other, but have varying variances [14]. For parameter estimation $\boldsymbol{\beta}(u_i, v_i, t_i)$, different weights are used at each observation point, with the parameter estimation calculation as follows:

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{W}(u_i, v_i, t_i) \boldsymbol{X}]^{-1} \boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{W}(u_i, v_i, t_i) \boldsymbol{y} \quad (2)$$

Here, $\boldsymbol{X}$ is the design matrix containing the independent variables (with the first column equal to 1 to represent the intercept), $\boldsymbol{X}^{\boldsymbol{T}}$ denotes the transpose of matrix $\boldsymbol{X}$. $\boldsymbol{y}$ is the vector of dependent variable values. The matrix $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$is a diagonal matrix $n \times n$ containing weights at each location and time point $i$and elements other than the diagonal are zero. With $w_{ij}$is the weighting of the data in $j$the modeling for the location and time point i. The elements in $\boldsymbol{W}(u_i, v_i, t_i)$ are calculated from kernel functions Gaussian spatial-temporal, as follows:

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}^S}{h_S}\right) - \frac{1}{2}\left(\frac{d_{ij}^T}{h_T}\right)\right) \tag{3}$$

And for kernel functions Bi-square spatial-temporal inner elements $\boldsymbol{W}(u_i, v_i, t_i)$are calculated from:

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}^S}{h_S}\right)^2 - \left(\frac{d_{ij}^T}{h_T}\right)^2\right)^2, if \left(\frac{d_{ij}^S}{h_S}\right)^2 + \left(\frac{d_{ij}^T}{h_T}\right)^2 \leq 1; j = 1,2, \dots, n \\ 0, others \end{cases} \tag{4}$$

With $w_{\ ij}$ is a weighting agent data j-th on modeling for observation point (u_i, v_i, t_i)-th. Thus, for one point i, the weight is calculated for $j = 1,2, \dots, n$. With, $d_{ij}^S = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$ is the spatial distance and $d_{ij}^T = |t_i - t_j|$ is the temporal distance. Bandwidth spatial (h_S) and bandwidth temporal (h_T) is determined based on corrected Akaike Information Criterion (AICc) [15]. The optimum bandwidth is determined based on the smallest AICc value.

$$AIC_c = 2n\log(\hat{\sigma}) + nlog(2\pi) + n\left(\frac{n + tr(\boldsymbol{L})}{n - 2 - tr(\boldsymbol{L})}\right) \tag{5}$$

Where n is the number of samples, $\hat{\sigma}$ is the estimated standard deviation of the error, and $trace(\boldsymbol{L})$ is the trace from the projection matrix $\boldsymbol{L}$.

$$\boldsymbol{L} = \boldsymbol{X}\left(\boldsymbol{X^T W}(u_i, v_i, t_i)\boldsymbol{X}\right)^{-1}\boldsymbol{X^T W}(u_i, v_i, t_i) \tag{6}$$

In the GTWR model, the estimated parameters are local, meaning their values differ at each observation location and time point. In some cases, data points that are too far from the observation location have little contribution to the estimation process because they receive low weight in the kernel function. Therefore, local standard errors not only reflect statistical variability but also show the local significance of the estimated regression coefficients [18].

To test the significance of the local parameters, the following test statistic is used.

$$t_{value} = \frac{\hat{\beta}_k(u_i, v_i, t_i)}{\hat{\sigma}\sqrt{B_{kk}}} \tag{7}$$

It is known B_{kk}that is the diagonal element $k$of the variance-covariance matrix $\boldsymbol{BB^T}$,
$\boldsymbol{B} = \left(\boldsymbol{X^T W}(u_i, v_i, t_i)\boldsymbol{X}\right)^{-1}\boldsymbol{X^T W}(u_i, v_i, t_i)$ and $\hat{\sigma}^2 = \frac{SSE}{trace[(\boldsymbol{I-L})^T(\boldsymbol{I-L})]}$
with,

$$SSE = \boldsymbol{Y^T}(\boldsymbol{I} - \boldsymbol{L})^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L})\boldsymbol{y}$$

Null hypothesis rejected if $|t_{value}| > t_{\delta_1^2/\delta_2(\alpha/2)}$ means local regression parameters β_k at location and time i do significantly influence the dependent variable. According to Leung et al. [21], $\delta_v = trace[(\boldsymbol{I} - \boldsymbol{L})^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L})]^v$ for v = 1, 2. Here, v serves as an index to generate two values, δ_1 and δ_2, which are employed to approximate the degrees of freedom of the test statistics in equation (7).

2.2. *Spatial-Temporal Heterogeneity*

Regression with ordinary least squares (OLS) modeling must fulfill classical assumptions to obtain the Best Linear Unbiased Estimator (BLUE). In OLS modeling on spatial data, the assumption of homoscedasticity is often violated due to the variance of the error differs depending on the observation location. This difference occurs because the data conditions at one location are not the same in terms of characteristics. Thus, the obtained regression parameters will vary partially. Spatial-temporal data refers to the concept of the relationship between events occurring at various points in space and time. Spatial-temporal data is described as data that encompasses both spatial and temporal aspects. Spatial data refers to information about the location of an event, while temporal data refers to the time of the event.

Spatial heterogeneity in data can be detected using the Breusch-Pagan (BP) test statistic [16]. The decision to reject the null hypothesis is made if the Breusch-Pagan (BP) statistic value is greater than χ^2_p, where p is the number of independent variables in the model. If a decision to reject is obtained H_0 in OLS modeling, there are differences in characteristics between one location and another, or there is heterogeneity in the data.

2.3. *Classical Assumptions*

A multicollinearity test was conducted before building the model. Multicollinearity is a condition where there is a perfect relationship (high correlation) between the independent variables in the model. This assumption was tested using the Variance Inflation Factor (VIF). A VIF of more than 10 is considered to indicate perfect collinearity between the independent variables. Regression analysis assumes that the error spread follows a normal distribution with a mean of zero and a variance of σ^2,$\varepsilon_i \sim N(0, \sigma^2)$ [17]. Therefore, checking the normality assumption error, both in the OLS and GTWR models, was performed using the Kolmogorov-Smirnov test. In addition, the Durbin-Watson (DW) test was applied to detect the presence of autocorrelation in the residuals of the regression model.

2.4. *Model performance*

In this study, the performance of GTWR and OLS was compared to determine which model better describes spatial-temporal heterogeneity. The model performance was evaluated using adjusted R^2. Adjusted R^2 for the OLS model [17], calculated from:

$$Adjusted\ R^2_{OLS} = 1 - (1 - R^2)\left(\frac{n-1}{n-p-1}\right) \quad (8)$$

With *n being* the number of observations and p the number of independent variables in the model. In the GTWR model, the number of parameters p depends on the spatial-temporal weight structure applied to each observation point. Therefore, the number of parameters in the GTWR model is estimated by the effective number of parameters = $\left(2tr(\boldsymbol{L}) - tr\left(\boldsymbol{L}^T\boldsymbol{L}\right)\right)$ [15]. Thus, the calculation of adjusted R^2 for the GTWR model:

$$Adjusted\ R^2_{GTWR} = 1 - (1 - R^2)\left(\frac{n-1}{n-\left(2tr(\boldsymbol{L}) - tr(\boldsymbol{L}^T\boldsymbol{L})\right)-1}\right) \quad (9)$$

An adjusted R^2 value approaching 1 indicates that the independent variables in the regression model can explain the variation in the dependent variable better.

Local regression modeling, particularly GTWR, accounts for spatial and temporal heterogeneity by allowing variable relationships to differ across locations and over time. Therefore, the local R^2 is used to measure the model 's ability to explain data variation specifically around a particular location [18]. The formula for local R^2, R_i^2, is:

$$R_i^2 = (TTS^w - SSE^w)/TTS^w \quad (10)$$

TSS^w is the geographically weighted total sum of squares, defined as: $TTS^w = \sum_j w_{ij}\left(y_j - \bar{y}\right)^2$.
SSE^w is the geographically weighted sum of squares of the errors, defined as:
$SSE^w = \sum_j w_{ij}\left(y_j - \hat{y}_j\right)^2$.
w_{ij} is the geographic weight between observation point j and regression point i.

3. Result and Discussion

3.1. *Overview of Dengue Fever Incidence Rate in West Java*

The spatial-temporal distribution of dengue fever incidence rates in regencies/cities in West Java from 2019 to 2023 was obtained to obtain a general spatial-temporal picture of dengue fever incidence rates, as well as climate change and social vulnerability factors. The map is colored using the natural breaks (Jenks) method to group dengue fever incidence rates into classes that describe the natural boundaries of data distribution. The years 2019 and 2023 were chosen as the focus of spatial visualization and interpretation.

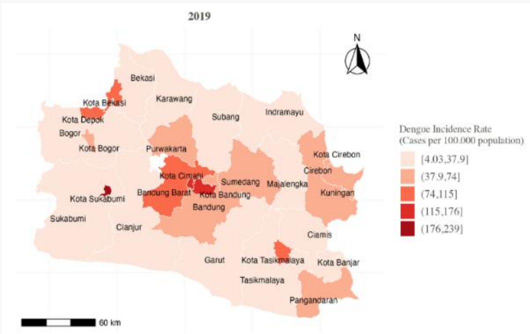


Figure 32. Spatial Distribution of Dengue Fever Incidence Rate in West Java, 2019.

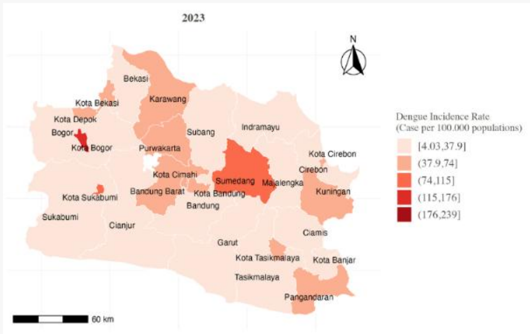


Figure 33. Spatial Distribution of Dengue Fever Incidence Rate in West Java, 2023.

In 2019 (Figure 32), most regencies/cities in West Java, Central Priangan Region, experienced high dengue fever incidence rates, indicated by the darker red color. Dengue fever incidence rates tended to be clustered in urban areas, such as Central Priangan (Bandung, Bandung City, and surrounding areas). The Bandung area and its surroundings are experiencing rapid land use changes into residential areas, resulting in the emergence of dense settlements that are not supported by basic sanitation, adequate access to clean water, and a clean environment, which ultimately increases the risk of dengue fever transmission [18]. In 2023 (Figure 33), a decrease in the intensity of dengue fever incidence rates was observed in several regencies/cities, indicated by a shift to lighter colors. While there was a general downward trend, several regions experienced increases, including Bogor City, which had the highest dengue fever incidence rate in 2023.

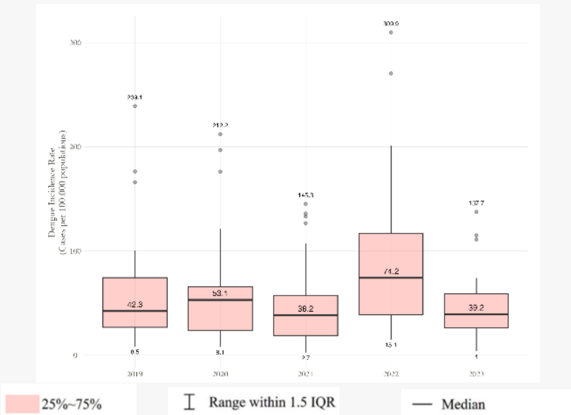


Figure 34. Temporal Distribution of Dengue Fever Incidence Rate in West Java, 2019 – 2023.

Boxplot visualization (Figure 34), in 2022, the median incidence rate was highest compared to other years. In contrast, 2021 showed the lowest incidence distribution. The decline in the number of dengue cases in 2021 reported in several regions was due to the increase in the number of COVID-19 cases, which had affected dengue epidemiological surveillance, resulting in underreporting of dengue cases [19]. In addition, the difficulty of timely diagnosis and public concern about the risk of COVID-19 infection were other reasons for the decline in the number of dengue cases. The dengue virus is generally carried by travelers [20]. Therefore, self-isolation and quarantine due to COVID-19 led to a decrease in the dengue incidence rate.

3.2. *The influence of climate change and social vulnerability factors on the dengue fever incidence rate*

To determine the influence of climate change and social vulnerability variables on dengue fever incidence rates without considering observation locations and time, regression modeling with ordinary least squares (OLS) was used. This model assumes that the influence of independent variables on dengue fever incidence rates is constant across regions and time. However, this assumption is generally unrealistic because parameters tend to vary across regions and time [17]. Therefore, the OLS model was used as a base model in this study, which serves as a starting point for comparison to assess whether the addition of spatial and temporal aspects to the GTWR model can improve performance in capturing local variations in the influence of climate change and social vulnerability on dengue fever incidence. By comparing the results of the performance between the OLS and the GTWR, we can determine the extent to which the spatial-temporal model can overcome the limitations of the parameter homogeneity assumption in the global model. The OLS is displayed in table 3:

Table 17. OLS model parameter estimation results.

Variables	Coefficient	Standard Error	t_{value}
Intercept	-130.912	87.230	-1.501
Land surface temperature	-1.288	2.847	-0.453
Rainfall	0.011	0.005	2.126*
Percentage of the poor population	2.326	2.184	1.065
Population density	0.005	0.002	2.659*
Percentage of households do not have access to proper sanitation	0.488	0.336	1.451
Ratio of the number of health facilities	0.776	0.263	2.952*
Percentage of the female population aged 25 years and over with at least a high school education	1.649	0.625	2.638*

* Regression parameter is statistically significant at significance level 5% and number of samples 135

The results of identifying non-multicollinearity based on the VIF values for each independent variable in the regression model. Based on the VIF limit of 10, all variables in the model do not experience perfect multicollinearity. The Kolmogorov-Smirnov test produced a statistical value of 0.087, which is smaller than the critical point (0.117) at a number of samples of 135 and a significance level of 5%. Because it failed to reject the null hypothesis, the error follows the normal distribution, and the assumption of normality error met. The statistical value of the Durbin–Watson test is 1.736, which is between lower and upper limits of the table Durbin-Watson, then according to the decision table it is in the inconclusive region, so it cannot be determined from the table whether there is autocorrelation or not. The *p-value* obtained was 0.048, which is less than the 5% significance level, so the decision was to reject the null hypothesis. Thus, based on the *p-value*, it can be concluded that there is significant autocorrelation in the OLS model error

The Breusch-Pagan (BP*)* test yields a statistical value of 21.256, which is greater than the critical value (14.067) at a significance level of 5%, thus rejecting the null hypothesis, meaning the homoscedasticity assumption is violated and the error variance is not constant. From this test, indicates heterogeneity in the data based on the distribution of data from year to year. Thus, a model is needed that can address spatial-temporal heterogeneity, one of which is the GTWR model.

3.3. The influence of climate change and social vulnerability factors on the dengue fever incidence rate based on GTWR model

The dengue fever incidence rate variable as the dependent variable, social vulnerability factors and climate change as independent variables are used to construct a regression relationship that takes into account regional and time aspects using the GTWR model. The first step of the analysis is to calibrate the GTWR model to obtain h_S and h_T minimize the AICc. Good kernel function Gaussian and Bi-square, used for GTWR model calibration. Based on the AICc criteria the selected spatial and temporal bandwidth values are h_S = 0.868 and h_T = 5 with an AICc of 1413.200 based on the kernel function Bi-square.

From this model, we obtain n = 27 (location) × 5 (time) = 135 equations based on location and time. The summary statistics of the GTWR model parameter estimates are presented in Table 18.

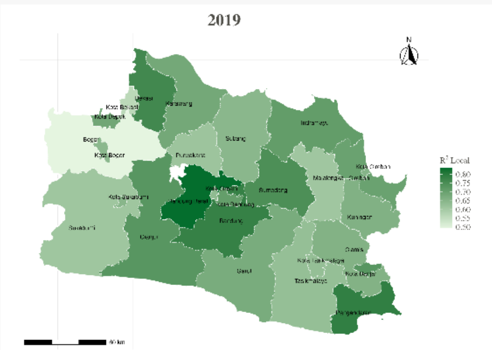
Table 18. Summary statistics of GTWR model parameter estimates.

Variables	Coefficient	Minimum	Median	Maximum
Intercept	$\hat{\beta}_0(u_i, v_i, t_i)$	-0.581	-0.185	-0.0002
Land surface temperature	$\hat{\beta}_1(u_i, v_i, t_i)$	-14.451	-5.463	-0.033
Rainfall	$\hat{\beta}_2(u_i, v_i, t_i)$	-0.015	0.011	0.028
Percentage of the poor population	$\hat{\beta}_3(u_i, v_i, t_i)$	-9,360	-0.072	14.046
Population density	$\hat{\beta}_4(u_i, v_i, t_i)$	-0.006	0.006	0.049
Percentage of households do not have access to proper sanitation	$\hat{\beta}_5(u_i, v_i, t_i)$	-2.417	0.359	2,582
Ratio of the number of health facilities	$\hat{\beta}_6(u_i, v_i, t_i)$	-0.387	0.676	2,262
Percentage of the female population aged 25 years and over with at least high school education	$\hat{\beta}_7(u_i, v_i, t_i)$	-0.796	1.630	6,067

3.4. Model performance

The GTWR model has R^2 and adjusted R^2 were 0.7006 and 0.5611 respectively which are much higher than the OLS model (R^2 = 0.445, adjusted R^2 = 0.4144). The R^2 value means that variables from climate change and social vulnerability factors can explain variations in the dengue fever incidence rate of 70.06 % based on the GTWR model.

The local R^2 map visually illustrates the model's ability to explain variations in dengue fever incidence rates, and demonstrates spatial heterogeneity in model goodness-of-fit across regions. Darker colors indicate better model goodness-of-fit, while lighter areas indicate lower model goodness-of-fit in explaining variations in dengue fever incidence rates within that region.



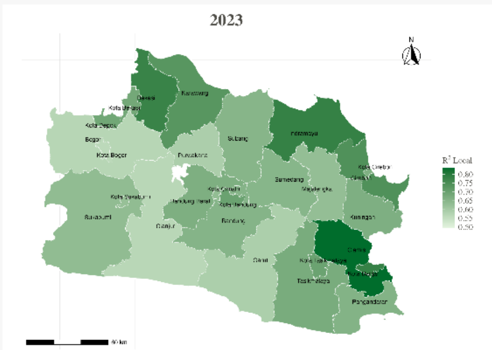


Figure 35. Local R^2 Distribution of The GTWR Model, 2019.

Figure 36. Local R^2 Distribution of The GTWR Model, 2023.

In 2019 (Figure 35), the region with the highest dengue fever incidence rate: Sukabumi City had a local R^2 of 0.803. Meanwhile, in 2023 (Figure 36), the region with the highest dengue fever incidence rate: Bogor City with a local R^2 value of 0.69. This indicates the good performance of the GTWR model in areas with a high burden of dengue fever incidence rate. However, lower local R^2 values in other areas indicate that the GTWR model has limitations in explaining variations in dengue fever incidence rates in those areas.

3.5. The influence of climate change and social vulnerability factors on the dengue fever incidence rate in each year

Boxplots of the regression coefficients of each variable from the climate change and social vulnerability factors are used to explore the trend of changes in the regression coefficients of the GTWR model over time. The regression coefficient for the same independent variable has a positive and negative coefficient direction due to the influence of differences in spatial-temporal location. Therefore, the characteristic differences in the spatial-temporal distribution of each regression coefficient and its influence in each regency/city can be identified quantitatively. The median of each boxplot reflects the direction and dominant influence of each variable in a given year.

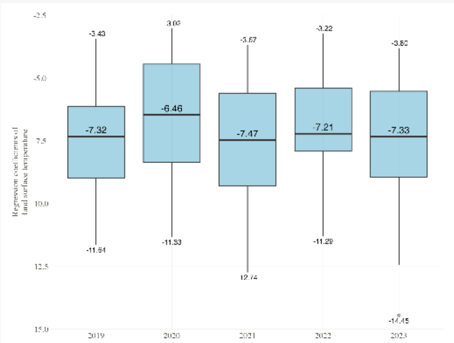


Figure 37. Temporal Distribution Of Significant Regression Coefficients of Land Surface Temperature.

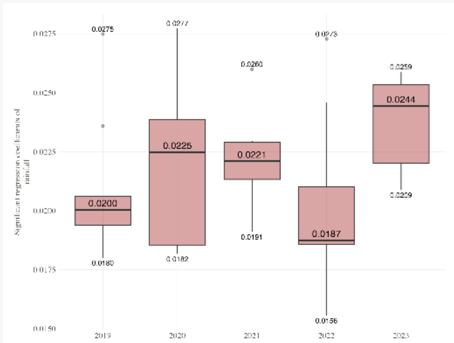


Figure 38. Temporal Distribution Of Significant Regression Coefficients of Rainfall.

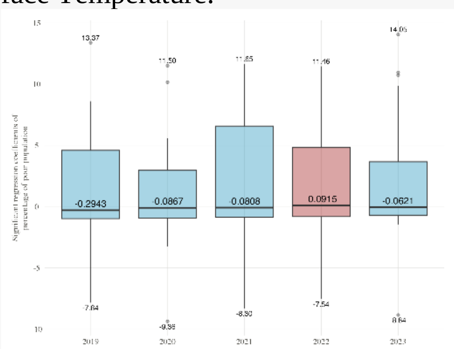


Figure 39. Temporal Distribution Of Significant Regression Coefficients of The Percentage of The Poor Population.

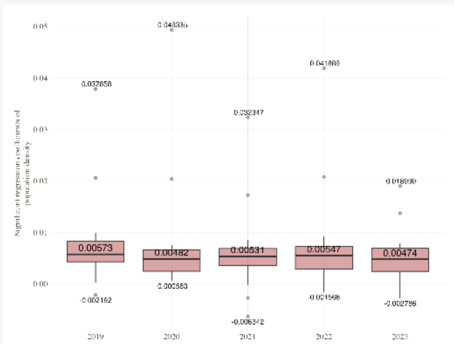


Figure 40. Temporal Distribution of Significant Regression Coefficients of Population Density.

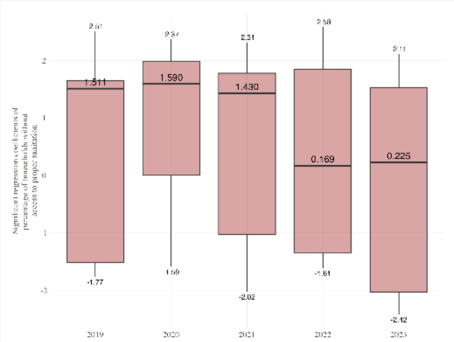


Figure 41. Temporal Distribution of Significant Regression Coefficients of The Percentage of Households do Not Have Access to Proper Sanitation.

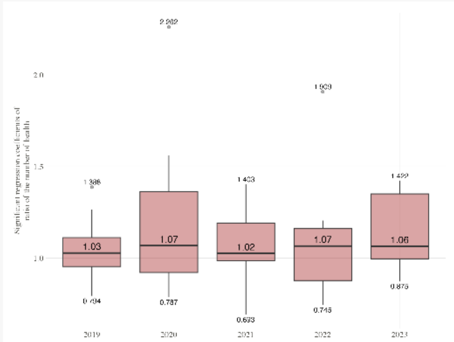
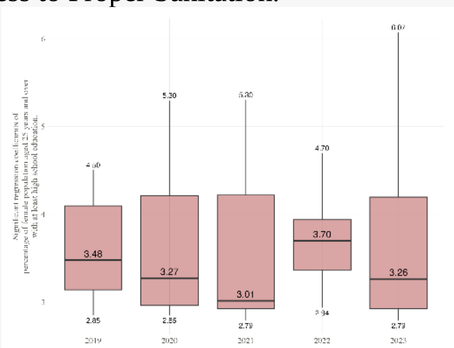


Figure 42. Temporal Distribution of Significant Regression Coefficients of The Ratio of Health Facilities.



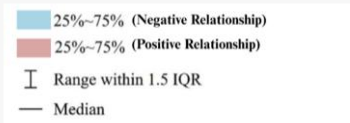


Figure 43. Temporal Distribution of Significant Regression Coefficients of The Percentage of The Female Population Aged 25 Years and Over with at Least a High School Education.

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Land surface temperature is an indicator in assessing the level of environmental exposure to the risk of vector-based diseases such as dengue fever. Higher surface temperatures support vector reproduction, such as egg laying, egg hatching, and larval development, thus encouraging virus transmission at higher temperatures [27]. Land surface temperature (Figure 37), the median coefficient is negative across years, meaning that the higher the land surface temperature, the lower the dengue fever incidence rate. This contradicts the theory, as these conflicting results are caused by the characteristics of each study location. However, these conflicting results can be explained by the characteristics of each study location, such as local adaptation of the vector. Pattern of relationship between temperature and the Aedes mosquito population in the form of an inverted "U" curve. Temperatures exceeding the optimal threshold (~30°C) can increase mosquito mortality and reduce their activity [28].

Furthermore, rainfall (Figure 38) also shows a consistently positive median coefficient each year, meaning that high rainfall influences the increase in dengue fever incidence. Increased rainfall influences the high rate of mosquito reproduction and dengue fever transmission. Rainfall is one indicator in assessing exposure to dengue fever. High rainfall affects the life cycle of the Aedes aegypti mosquito, the primary vector of dengue fever. Rain can create stagnant water in natural and artificial containers—such as flower pots, used cans, or water reservoirs—which serve as breeding grounds for mosquitoes [5]. Rainfall is an external factor of climate hazards that interacts with social conditions and the adaptive capacity of the community, thus determining the level of dengue fever risk [9].

Weak economic conditions limit the ability of individuals and communities to access essential resources, including health services, clean water, sanitation, adequate housing, disease prevention information, and economic protections such as insurance or social assistance programs [10]. The percentage of the poor population (Figure 39) has predominantly a negative coefficient value in each observation year. This means that a higher percentage of the poor population will reduce the incidence of dengue fever. This contradicts the theory, these conflicting results are caused by the characteristics of each study location, such as the level of dengue fever susceptibility in the population, the implementation and coverage of vector control measures, and differences in the spatial units of the study or socioeconomic variables considered [29]. Research suggests that higher poverty status has a negative effect on dengue transmission [30]. Poor people tend to be reluctant to seek health services when infected with dengue fever and thus dengue infections are underreported [31]. However, in 2022, the effect of the percentage of poor people showed a difference, with the regression coefficient having a positive median value. This means that a higher percentage of poor people will increase the incidence of dengue fever. This can be caused by various factors, such as a decrease in the coverage of vector control interventions in poor areas after the COVID-19 pandemic, as well as the high burden on health services due to COVID-19 which causes uneven distribution of prevention services [32].

Population density (Figure 40) shows a consistently positive median coefficient each year, meaning that population density began to influence the increase in dengue fever incidence rates. Population density is an indicator in measuring an area's exposure to dengue fever transmission. This is because humans function as hosts for the virus, so the more densely populated an area is, the greater the chance of transmission from one person to another through mosquito bites [33]. Areas with high population density, generally in urban areas, are areas with a high level of exposure to dengue fever [5]. The structure of the city influences the incidence of dengue fever, areas with high building density and low vegetation cover have a higher level of dengue susceptibility [34]. Informal or dense settlements tend to lack basic infrastructure such as good drainage, closed sanitation systems, and adequate waste management, thus increasing the possibility of the formation of stagnant water as a breeding ground for mosquitoes. Population density is directly linked to the likelihood of the population interacting with dengue vectors [5].

The percentage of households without access to proper sanitation (Figure 41) shows a consistently positive median coefficient each year, meaning that regencies/cities with poor sanitation have an impact on increasing the incidence of dengue fever. Poor sanitation indicates proximity to poor water resources and poor housing quality [35]. Lack of access to basic services, such as proper sanitation allows vectors to easily find good places to lay eggs in areas with high levels of social vulnerability [14]. Lack of access to adequate sanitation is a key indicator in assessing a region's sensitivity to vector-borne diseases such as dengue fever. Poor sanitation reflects structural vulnerabilities inherent in a community's social conditions, particularly in poor and densely populated areas. Social systems and inequalities in access to basic infrastructure, such as clean water and sanitation increase a community's sensitivity to disasters and disease.

Access to adequate health services is a key factor in building community resilience against waterborne diseases, including dengue fever. The availability of affordable and high-quality healthcare facilities plays a role in reducing disease fatalities and increasing communities' capacity to adapt to environmental health risks [5]. The ratio of the number of health facilities (Figure 42) shows a negative median coefficient across the years. This means that regencies/cities with a higher ratio of health facilities tend to have lower dengue fever incidence rates. This result is in line with findings Wijayanti et al. [15] showing that distance to health facilities is an important factor in reporting dengue cases. The greater the distance, the greater the likelihood of cases going unreported. Therefore, high availability of health facilities can improve access to medical services and early detection, thereby reducing the risk of dengue fever spread.

A key aspect of adaptive capacity is education, particularly for women, which significantly influences household-level decision-making in the context of health. An individual's level of education, particularly for women, is closely related to their ability to access information, understand disease risks, and implement effective preventive practices [5]. Education provides the foundation for health literacy, enabling individuals to assess available information, understand disease symptoms and transmission, and actively participate in disease prevention and control efforts in their communities. But, the percentage of the population aged 25 years and over with at least a high school education (Figure 43) shows a positive median coefficient throughout the observation years. In general, a higher percentage of the population aged 25 years and over with at least a high school education will influence the increase in the incidence of dengue fever. Similar findings were also reported by Carabali et al. [31], residents with higher levels of education are more likely to seek health services when infected with dengue fever. Regions with higher levels of education tend to have better reporting and recording systems for dengue cases.

3.6. The influence of climate change and social vulnerability factors on the dengue fever incidence rate in each regency

Differences in characteristics in each regency/city cause spatial variations in the strength and direction of influence between variables from climate change factors and social vulnerability on the incidence of dengue fever. The regression coefficients that influence the incidence of dengue fever, with a positive direction for each variable in 2019 and 2023 are selected for analysis. In this case, the main focus of the study is to identify areas with the largest number of significant variables, especially those with a positive direction, because the more variables that have a significant positive effect on the incidence of dengue fever indicate a high level of vulnerability to dengue fever in that area. Of the total seven variables (intercept not included) analyzed, the maximum number of positive significant variables found in a region was four. Therefore, the grouping of dengue fever intervention priority scale levels was set as follows: areas with three to four positive significant variables were categorized as high, while areas with one to two variables were categorized as low. The following is a summary of priority areas for dengue fever intervention based on the results of local parameter estimation of the GTWR model:

Table 19. Changes in the number of regression parameter with a statistically significant positive influence by regency/city.

Region	Number of Variables with a Significant Positive Influence	
	2019	2023
Cianjur Regency	3	3
Tasikmalaya Regency	1	4
Ciamis Regency	1	3
Garut Regency	2	3
Kuningan Regency	0	3
Banjar City	1	3
Tasikmalaya City	1	3
Sukabumi City	3	1
Bandung Regency	0	1
West Bandung Regency	1	0
Bekasi Regency	1	1
Bogor Regency	2	1
Cirebon Regency	0	0
Indramayu Regency	0	1
Karawang Regency	1	0
Majalengka Regency	1	1
Pangandaran Regency	1	2
Purwakarta Regency	2	1
Subang Regency	2	1
Sukabumi Regency	2	1
Sumedang Regency	2	1
Bandung City	0	0
Bekasi City	2	1
Bogor City	2	1
Cimahi City	0	0

Table 19. Changes in the number of regression parameter with a statistically significant positive influence by regency/city.

Region	Number of Variables with a Significant Positive Influence	
	2019	2023
Cirebon City	0	0
Depok City	1	0

Based on table 5, the results in areas have a high number of positive significant variables in 2019 and remain high in 2023 like Cianjur Regency and areas that in 2019 had a low number of significant variables but increased significantly in 2023 like Tasikmalaya Regency, Ciamis Regency, Garut Regency, Kuningan Regency, Banjar City, and Tasikmalaya City should be the primary focus of dengue control intervention efforts. These areas demonstrate high levels of vulnerability, both consistently and due to an increase in the number of significant positive variables over the past five years. This indicates that variables from climate change and social vulnerability factors in these areas further strengthen the potential for increased dengue incidence. Meanwhile, areas with both years had a low or no number of positive significant variables can be used as control or comparison areas in policy evaluations, but still need to be monitored for changes in environmental and social factors.

4. Conclusion

This study explores and analyzes the spatial-temporal distribution of dengue fever incidence rates and the influence of climate change factors and potential social vulnerabilities in West Java in 2019–2023. This study revealed that the distribution of dengue fever incidence rates in West Java is heterogeneous and clustered. In 2019, most regencies/cities in West Java had high dengue fever incidence rates. Dengue fever incidence rates tended to be clustered in urban areas, such as Bodebek (Bogor, Depok, Bekasi) and Central Java. Priangan (Bandung, Bandung City, and surrounding areas). However, in 2023, there was a decrease in the intensity of dengue fever incidence rates in most areas of West Java.

The variables rainfall, population density, percentage of households with inadequate sanitation access, percentage of population with at least a high school education, and ratio of health facilities show a positive influence on the incidence rate. Dengue fever occurs in most areas and at most times. In contrast, land surface temperature and the percentage of poor people showed a negative influence on the incidence rate of dengue fever in most areas and times.

The GTWR model results can guide the government in developing regional and time-based policies, prioritizing interventions in dengue-prone areas, and collaborating with the Meteorology, Climatology, and Geophysics Agency (BMKG) to monitor microclimates and build weather-based early warning systems. Further research can expand the scope of indicators, such as population mobility, urbanization levels, land cover, the presence of stagnant water, air humidity, and vector mosquito density, used to describe social vulnerability factors and climate change, to better capture local variations in dengue incidence rates.

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