Journal Home Page:
https://e-journal.unair.ac.id/JKL

Jurnal Kesehatan Lingkungan
Journal of Environmental Health
Vol. 18 No. 3
DOI: 10.20473/jkl.v18i3.2026.275-285
ISSN: 1829 - 7285 | E-ISSN: 2540 - 881X

ORIGINAL RESEARCH Open Access

CLIMATE VARIABILITY AND DENGUE DYNAMICS: A PATH ANALYSIS IN SURABAYA, INDONESIA

Khuliyah Candraning Diyanah[1], Ririh Yudhastuti[2*], Lilis Sulistyorini[2], Mahmudah[3], Heny Arwati[4], Hari Basuki Notobroto[3], Rahmat Dapari[5], Fariani Syahrul[3], Muhammad Rasyid Ridha[6], Babucarr Jassey[7], Aditya Sukma Pawitra[2], Diva Alishya Shafwah[8], Nafi'atul Irbah[9]

[1]Doctorate Degree Program in Public Health, Faculty of Public Health, Universitas Airlangga, Surabaya 60115, East Java, Indonesia
[2]Department of Environmental Health, Faculty of Public Health, Universitas Airlangga, Surabaya 60115, East Java, Indonesia
[3]Department of Epidemiology, Biostatistics, Population Studies and Health Promotion, Faculty of Public Health, Universitas Airlangga, Surabaya 60115, East Java, Indonesia
[4]Department of Medical Microbiology and Parasitology, Faculty of Medicine, Universitas Airlangga, Surabaya 60132, East Java, Indonesia
[5]Department of Community Health, Faculty of Medicine and Health Sciences, Universiti Putra Malaysia, Serdang 43400, Selangor, Malaysia
[6]Department of Epidemiology, Public Health Study Program, Faculty of Medicine and Health Sciences, Universitas Lambung Mangkurat, Banjarbaru 70714, South Kalimantan, Indonesia
[7]Department of Public Health Services, Ministry of Health, Banjul, The Gambia
[8]Independent Researcher in Environmental Health Science
[9]Faculty of Public Health, Universitas Airlangga, Surabaya 60115, East Java, Indonesia

Corresponding Author:
*) ririhyudhastuti@fkm.unair.ac.id

Article Info

Submitted	: 1 April 2026
In reviewed	: 25 April 2026
Accepted	: 31 May 2026
Available Online	: 31 July 2026

Keywords : *Climate Variability, Dengue, Path Analysis, Tropical Megacity, Urban Microclimate*

Published by *Faculty of Public Health Universitas Airlangga*

Abstract

Introduction: *Dengue fever is a climate-sensitive vector-borne disease. While many studies have documented associations between climate variables and dengue incidence, most rely on conventional regression approaches that fail to separate direct and indirect climatic pathways, limiting mechanistic understanding and utility for environmental health. This study aims to elucidate the interconnected effects of climatic variability on dengue incidence in Surabaya. This study integrates seasonal time-series decomposition and path analysis to distinguish direct and indirect climatic pathways, sunlight duration and wind speed.* ***Methods:*** *A retrospective ecological design, monthly dengue incidence data from 2020 to 2024 were integrated with meteorological variables, including rainfall, temperature, humidity, sunlight duration, and wind speed. Seasonal time-series decomposition was applied to characterize temporal dynamics, followed by path analysis within a structural equation modeling framework to quantify direct and indirect climatic effects.* ***Results and Discussion:*** *A pronounced seasonal pattern in dengue incidence, with peaks during the rainy season. Maximum temperature, relative humidity, sunlight duration, and minimum wind speed exerted significant direct effects on dengue incidence ($p < 0.05$). Rainfall showed no direct association but acted as a key upstream driver influencing other climatic variables. The structural model explained 52.1% of the variance in dengue incidence, highlighting the contribution of interconnected climatic processes.* ***Conclusion:*** *These findings demonstrate that dengue dynamics in tropical metropolitan environments are governed by complex climate-mediated pathways rather than isolated climatic predictors. This study novel environmental epidemiological evidence to support climate-informed dengue early warning systems and adaptive vector control strategies under climate variability and urban environmental change.*

INTRODUCTION

Dengue is an acute systemic viral infection transmitted to humans through the bite of the Aedes aegypti and Aedes albopictus mosquitoes, the world's fastest-growing mosquito species. Globally, the disease has spread to both endemic and epidemic levels, occurring more frequently in tropical and subtropical regions than in temperate climates (1–2). Change can impact terrestrial and marine ecosystems due to changes in temperature, humidity, rainfall patterns, and wind direction dynamics. The growth and development of both Aedes species are strongly influenced by temperature

Cite this as :
Diyanah KC, Yudhastuti R, Sulistyorini L, Mahmudah, Arwati H, Notobroto HB, et al. Climate Variability and Dengue Dynamics: A Path Analysis in Surabaya, Indonesia. *Jurnal Kesehatan Lingkungan*. 2026;18(3):275-285. https://doi.org/10.20473/jkl.v18i3.2026.275-285

and humidity. A warming climate and high rainfall can indirectly increase the risk of dengue fever transmission (3–4). A global study shows that climate variability factors, including global climate phenomena (El-Niño cycle) *ño Southern Oscillation* (ENSO) contributes to an increased risk of dengue outbreaks in several tropical and subtropical regions. In Indonesia, including Surabaya, ENSO events influence local rainfall patterns, temperature variability, and seasonal transitions. El Niño events are generally associated with reduced rainfall and prolonged dry seasons, whereas La Niña events increase precipitation intensity and duration. These climate anomalies may indirectly alter mosquito breeding habitats and dengue transmission dynamics through changes in local microclimatic conditions. However, the mechanism of the relationship between climate factors and dengue incidence is very complex, non-linear, influenced by spatial heterogeneity and has significant temporal dynamics (5–6).

Southeast Asia, including Indonesia, accounts for a significant proportion of dengue cases globally. A study found that dengue fever cases increased significantly in Southeast Asia between 2015 and 2019 (7). Metropolitan cities in Indonesia tend to face various risks, including overcrowding, rapid urbanization, and a seasonal tropical climate. There is a correlation between population density and mosquito flight distance, indicating that dengue transmission is more likely in cities with high populations (8). A spatial study in Indonesia shows that city clusters with moderate to high dengue fever incidence rates and high case densities are generally located in densely populated urban areas (3). Epidemiological studies in Surabaya, Indonesia's second-largest metropolitan city, show that it is endemic for dengue fever, with case numbers varying from year to year. This variation is quite high compared to other cities in Indonesia (9).

A statistical association between several climate variables and dengue fever incidence was demonstrated in a study in Bandung City, Indonesia, from 2021 to 2023 using multiple linear regression. These findings demonstrate that climate variability is a predictor of dengue fever incidence (10). Several countries used various regression, correlation, and time series models and found a strong correlation between several climate variables (often related such as temperature, humidity, and rainfall) and the number of dengue cases (11–14). Another study in Surabaya City, Indonesia, from 2009 to 2017 showed that average temperature, rainfall, and humidity were related to the incidence of dengue fever (15). But another study in the same city in 2007-2017 showed that rainfall and temperature were not related while humidity was related to dengue fever (9). Some of these research articles. Studies are generally limited to association analysis. They have not yet fully explored the causal analysis that explains the relationship between climate variables as a whole and the risk of dengue fever. It appears that other climate variables, such as wind speed and solar radiation, are not evaluated. This indicates a need for research that incorporates a broader range of climate variables and their relationship to dengue epidemiological models. Most studies on dengue fever are limited to large cities in Indonesia, with monthly and multi-year data resolutions and are still very limited, particularly in integrating multiple climate parameters simultaneously. Although previous studies have identified associations between climate variables and dengue incidence, many models remain focused on prediction or correlation analysis and provide limited understanding of direct and indirect climatic pathways required for operational early warning systems.

Despite extensive evidence demonstrating a relationship between climate variables and dengue incidence, current studies largely rely on correlation or regression approaches that treat climate factors as independent predictors, thus simplifying the inherent interconnectedness of the urban climate system. This limitation hinders a mechanistic understanding of how climate factors operate through direct and indirect pathways, particularly in tropical urban environments where rainfall, temperature, humidity, wind dynamics, and solar radiation interact nonlinearly. Furthermore, key urban microclimate variables such as wind speed and sunshine duration remain underexplored, while rainfall is often modeled as a direct determinant despite its context-dependent and mediated effects.

To address this gap, this study proposes a systems-based environmental epidemiology approach by integrating seasonal time series decomposition with path analysis (structural equation modeling) to explicitly separate direct and indirect climate pathways affecting dengue incidence. Using Surabaya a large tropical coastal city characterized by monsoon climate variability and dense urbanization as a representative environment, this study provides new empirical evidence on how upstream climate factors shape dengue dynamics through interconnected microclimate processes, thereby strengthening the scientific basis for climate-based early warning systems and adaptive vector control strategies in a rapidly developing tropical region. This is among the first studies in Indonesia to evaluate interconnected climatic pathways influencing dengue transmission using a structural equation modeling framework in a large tropical coastal city.

Therefore, the objectives of this study are to analyze the temporal and seasonal patterns of dengue fever incidence in Surabaya City for the period 2020–2024, to examine the direct and indirect effects of climate factors on dengue fever incidence using path analysis, and to identify key climate variables that have the potential to be used as indicators in a climate-based dengue early warning system.

METHODS

Study Area and Period

This study was conducted in Surabaya, the second largest metropolitan city in Indonesia, located on the northern coast of East Java (7°15′–7°21′S, 112°36′–112°54′E). Surabaya has a tropical monsoon climate characterized by two distinct seasons: a wet season from November to April and a dry season from May to October. The average annual rainfall ranges between 1,500 and 2,000 mm, with temperatures fluctuating between 24°C and 34°C. The city's dense population, estimated at approximately 3.1 million in 2020 and gradually increasing throughout the study period, provides favorable ecological and social conditions for mosquito breeding and dengue transmission. The study covered a five-year period, from January 2020 to December 2024, to capture temporal variations and long-term trends in dengue incidence and associated climatic factors. Although the five-year observation period does not capture long-term climate change trends, it is sufficient to evaluate seasonal climate variability and short-term climate–dengue relationships within an urban tropical setting.

Data Sources

Two main types of data were utilized in this study: epidemiological and climatic. Dengue data were obtained from the Surabaya City Health Department and consisted of monthly and annual records of both Dengue Fever (DF) and Dengue Hemorrhagic Fever (DHF) cases, along with reported deaths. Cases were further categorized by sex (male, female) and age groups (< 5 years, 5–14 years, 15–64 years, > 64 years). To ensure comparability across years, population data were retrieved from the Central Statistics Agency (BPS) and used as the denominator to calculate incidence rates (IR) per 100,000 population. Case fatality rates (CFR) were also calculated as the proportion of deaths among reported cases.

Climate data were collected from the Meteorological, Climatological, and Geophysical Agency of Indonesia (BMKG) Surabaya Station. The dataset included monthly observations of rainfall (mm), average temperature (°C), maximum and minimum temperature (°C), relative humidity (%), sunlight duration (hours), and wind speed (m/s). These variables were selected based on their established relevance to the life cycle of Aedes aegypti mosquitoes and previous studies linking climate variability with dengue outbreaks. Climate data was obtained from the BMKG Meteorological Station Perak I Meteorological Station. Climate data can be downloaded for free at https://dataonline.bmkg.go.id/dataonline-home

Variables

The primary dependent variable was dengue incidence (number of cases per 100,000 population). Independent variables included multiple climatic parameters: rainfall, mean temperature, maximum temperature, minimum temperature, humidity, sunlight, and wind speed. Epidemiological indicators such as incidence rate (IR) and case fatality rate (CFR) were calculated using the following formula: Incidence Rate (IR) = (Number of new cases ÷ Population) × 100,000; Case Fatality Rate (CFR) = (Number of deaths ÷ Number of cases) × 100. These indicators were used to evaluate both the magnitude and severity of dengue transmission across years.

Data Analysis

Data analysis was carried out in several stages, combining descriptive epidemiology, time-series methods, and statistical modeling. Annual and monthly distributions of dengue cases were described by category (DF, DHF, deaths), sex, and age group. The incidence rate (IR) and case fatality rate (CFR) were calculated using standard epidemiological formulas.

To explore the temporal dynamics of dengue cases, seasonal-trend decomposition was applied. An additive decomposition model was selected because the magnitude of seasonal fluctuations remained relatively stable throughout the observation period. This method separates the observed time series into three key components: trend-cycle, seasonal variation, and irregular fluctuations. By doing so, it allows the identification of long-term trajectories, recurrent seasonal peaks (eg, during rainy seasons), and unexpected anomalies beyond regular patterns.

$$Yt = Tt + St + It$$

Where Yt represents observed dengue cases at time t, Tt is the long-term trend component, St is the seasonal factor repeating annually, and it is the irregular (residual) component.

A path analysis framework was employed to test the causal relationship between climatic factors and dengue incidence. Rainfall was modeled as an exogenous variable influencing other climatic factors such as temperature, humidity, and wind speed. These intermediate variables, in turn, were hypothesized to directly affect dengue incidence. Path coefficients, t-statistics, and p-values were used to assess the strength and significance of each relationship. Statistical analyzes were performed using SmartPLS version 3.0 and R version 4.3, with a significance threshold set at $p < 0.05$. The general form of the structural equation can be expressed as:

$$Y2 = \beta1X2 + \beta2X4 + \beta3X5 + \beta4X7 + \varepsilon$$

Where Y2 = dengue incidence, X2 = maximum temperature, X4 = humidity, X5 = sunlight duration, X7 = minimum wind speed, and ε = error term. Additionally, rainfall (Y1) was modeled as an exogenous predictor of several climatic factors:

$$Xi = \alpha iY1 + \varepsilon i$$

Where Xi (i = 1–8) denotes climatic variables such as mean temperature, maximum temperature, minimum temperature, humidity, sunlight, and wind speed. The significance of each path was assessed using t-statistics:

$$t = \hat{\beta} / SE(\hat{\beta})$$

Where $\hat{\beta}$ is the estimated path coefficient and $SE(\hat{\beta})$ its standard error. Paths with $|t| \geq 1.96$ at $p < 0.05$ were considered statistically significant.

The adequacy of the path model was assessed using R-square and adjusted R-square values for endogenous variables. This ensured that the model accounted for a meaningful proportion of variance in dengue incidence. Multicollinearity was checked prior to model estimation to avoid overlapping influences among predictors. Model adequacy was evaluated using the coefficient of determination (R^2):

$$R^2 = 1 - \Sigma(Yi - \hat{Y}i)^2 / \Sigma(Yi - \bar{Y})^2$$

Where Yi are observed values, $\hat{Y}i$ are predicted values, and $\bar{Y}$ is the mean of observed values.

RESULTS

Table 1 and Figure 1 shows that the number of dengue cases in Surabaya City during the 2020–2024 period fluctuates consistently with seasonal patterns. On a monthly basis, cases tend to increase at the beginning of the year, peaking during the rainy season, then decline in the middle to end of the year when rainfall decreases. On an annual basis, case trends vary between years, with higher spikes in cases in certain years compared to the previous year, likely influenced by climatic conditions, population density, and the effectiveness of vector control interventions. This pattern confirms that seasonal and climatic factors play a significant role in the dynamics of dengue transmission in tropical urban areas such as Surabaya.

Based on Figure 2, the climate pattern in Surabaya City during the 2020–2024 period shows consistent seasonal variations. Average monthly rainfall peaked in January-March at 250–350 mm, while during the dry season (July-September) it dropped drastically to below 50 mm. Relative humidity follows this pattern, with peak levels reaching over 85% during the rainy season and decreasing to around 70% during the dry season. Average monthly temperatures are relatively stable between 27–29°C, with maximum temperatures tending to rise to 33–34°C during dry months, while minimum temperatures can drop to 24–25°C during wet months.

Table 1. Annual Dengue Fever Cases (Category, Sex): Population, Incidence (Per 100,000 Population), and Death Toll, 2020–2024

Variables	Years					p
	2020	2021	2022	2023	2024	
Case						
Dengue hemorrhagic fever (DHF)	73	111	195	191	231	
Die	0	0	1	0	0	
Gender						P > 0.1
Male	51	69	112	104	128	
Female	22	42	83	87	103	
Total Population	2,904,751	2,918,543	2,928,058	2,936,833	2,921,996	
IR* per 100,000 Population	2.51	3.8	6.7	6.5	7.9	
CFR (%)	0	0	0.51	0	0	
ABJ (%)	96%	96.5	97.68	98.22	98.38	

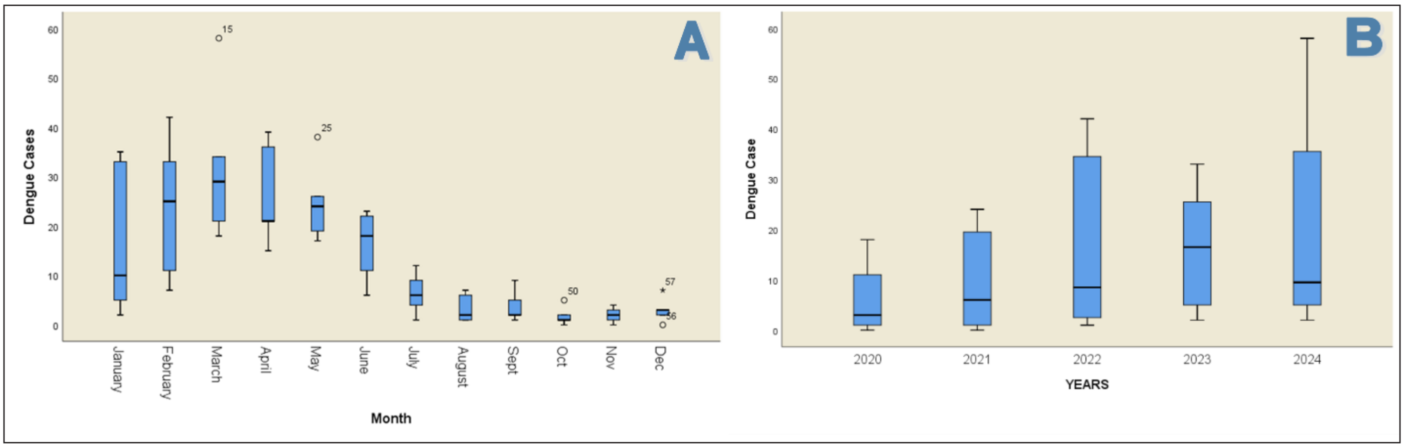

Figure 1. Dengue Cases 2020-2024 in Surabaya, Indonesia. A. Monthly, B. Annually

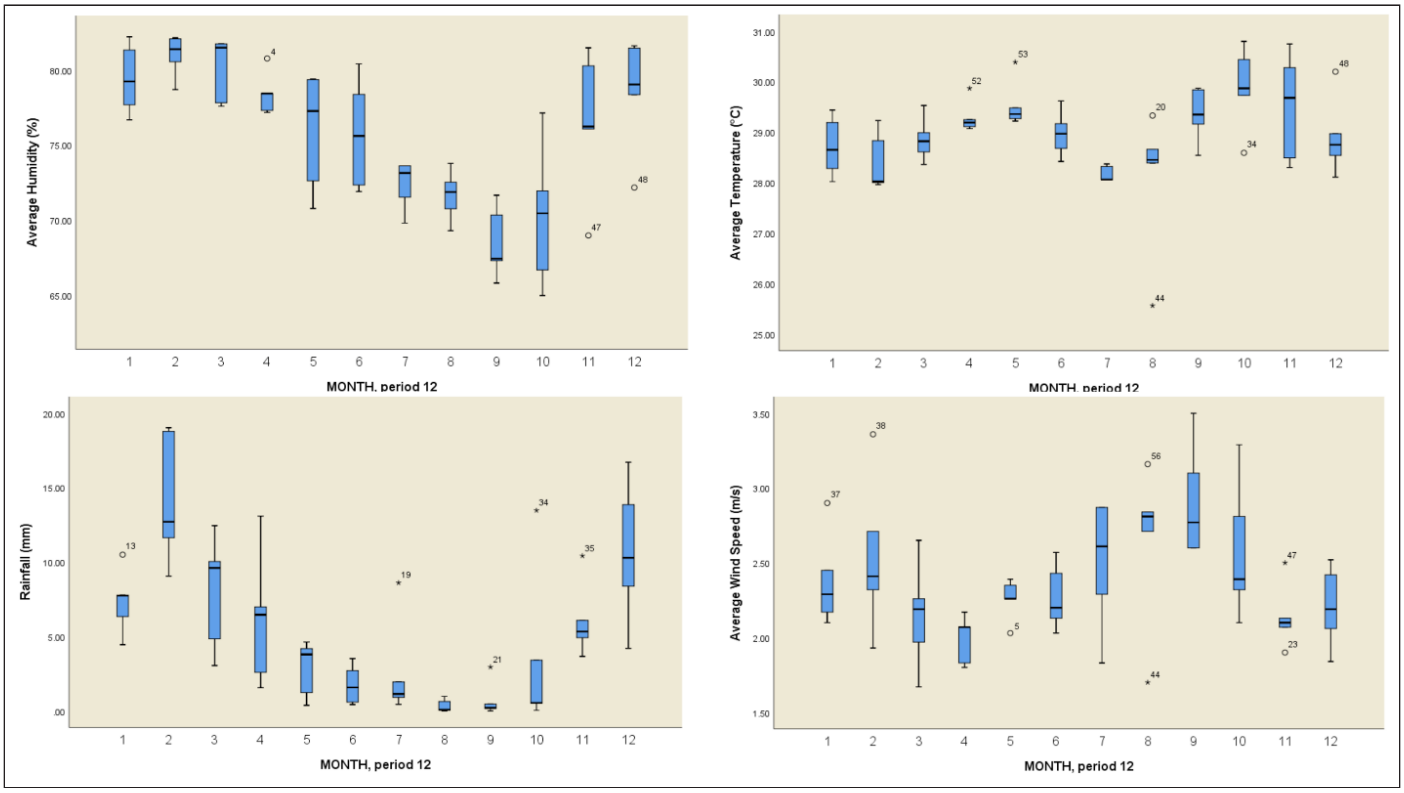

Figure 2. Monthly Climate Data from 2020-2024 in Surabaya City, Indonesia

The duration of sunshine shows the opposite trend, decreasing to less than 5 hours per day during months with high rainfall, but increasing to more than 8 hours per day during the dry season. These climate dynamics have significant epidemiological implications: high rainfall and favorable humidity create optimal breeding habitats for Aedes aegypti, while warm and stable temperatures accelerate the mosquito life cycle and dengue virus replication. Therefore, the peak rainy season reflected in these climate data plays a key role in explaining the increase in dengue incidence in Surabaya.

Figure 3 decomposes the time series data of dengue cases from 2020 to 2024 into three key components: trend (trend-cycle), seasonal factors, and seasonally adjusted data. Trends reveal the long-term movement of dengue cases, indicating whether there has been an overall increase, decrease, or stability over the past five years. The seasonal component extracts consistent recurring patterns each year, such as peak months (e.g., early in the year) and low months (e.g., mid-year), which are associated with climatic factors like the rainy season. Meanwhile, seasonally adjusted data removes the effects of these recurring patterns to identify anomalies or events outside the usual pattern, such as unexpected outbreaks that may be triggered by non-climatic factors like environmental changes or the effectiveness of prevention programs. Overall, this decomposition allows for a more in-depth analysis of dengue case dynamics by separating data variation into trends, seasonal cycles, and irregular fluctuations.

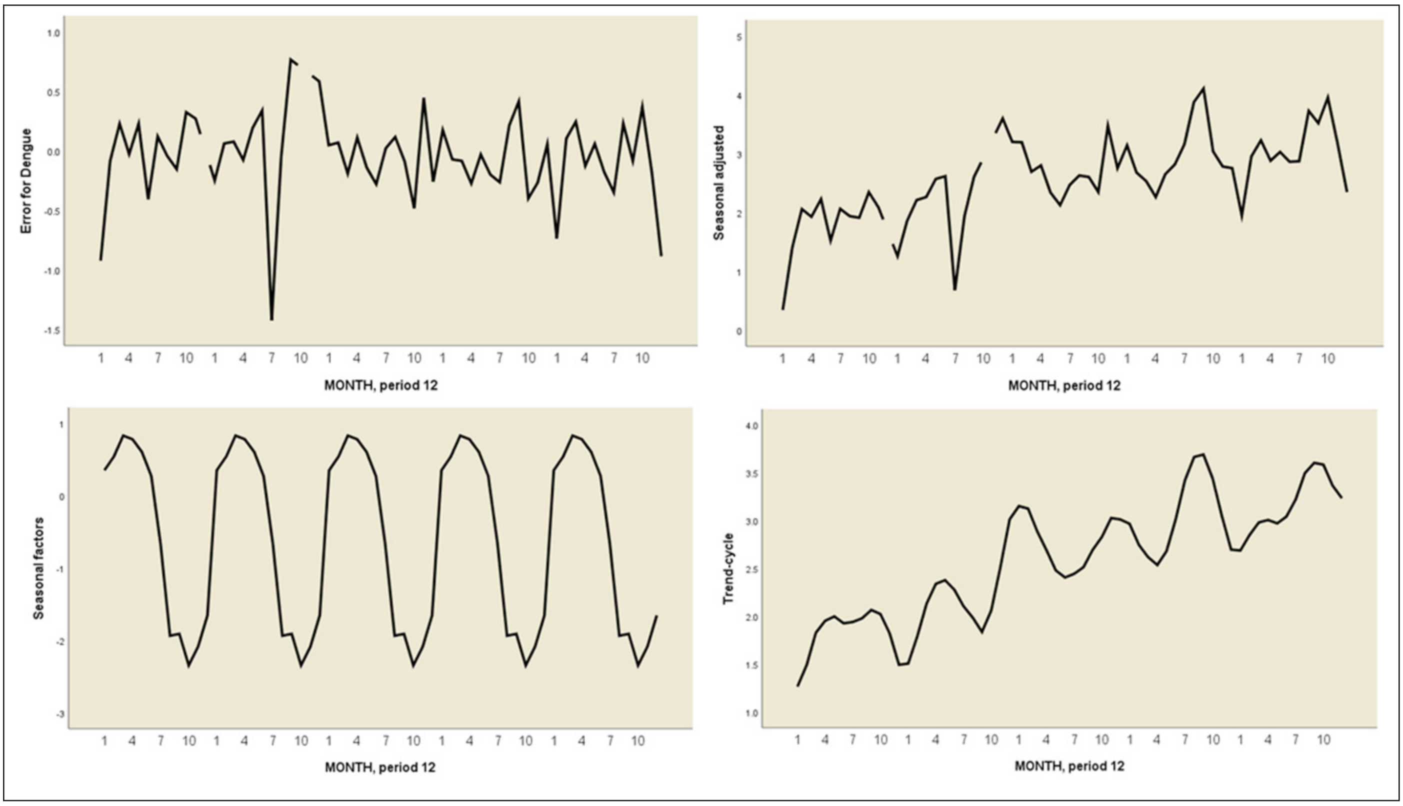

Figure 3. Regional Decomposition of Dengue Cases 2020-2024 in Surabaya, Indonesia

Figure 4 is a structural equation modeling (SEM) diagram that visualizes the causal relationships between variables as tested in the table. This diagram shows that the rainfall variable (Y1) is modeled as a factor that influences four other weather variables, namely Average Temperature (X1), Maximum Temperature (X2), Minimum Temperature (X3), and Humidity (X4). Furthermore, all eight weather variables (X1 to X8) have a direct path to the final variable, namely Dengue cases (Y2). The numbers indicated by each arrow are T-Statistic values that indicate the strength and significance of each relationship; values above approximately 1.96 (such as 2.363 for X2->Y2 or 5.124 for X7->Y2) indicate a significant relationship, consistent with the results presented in the table.

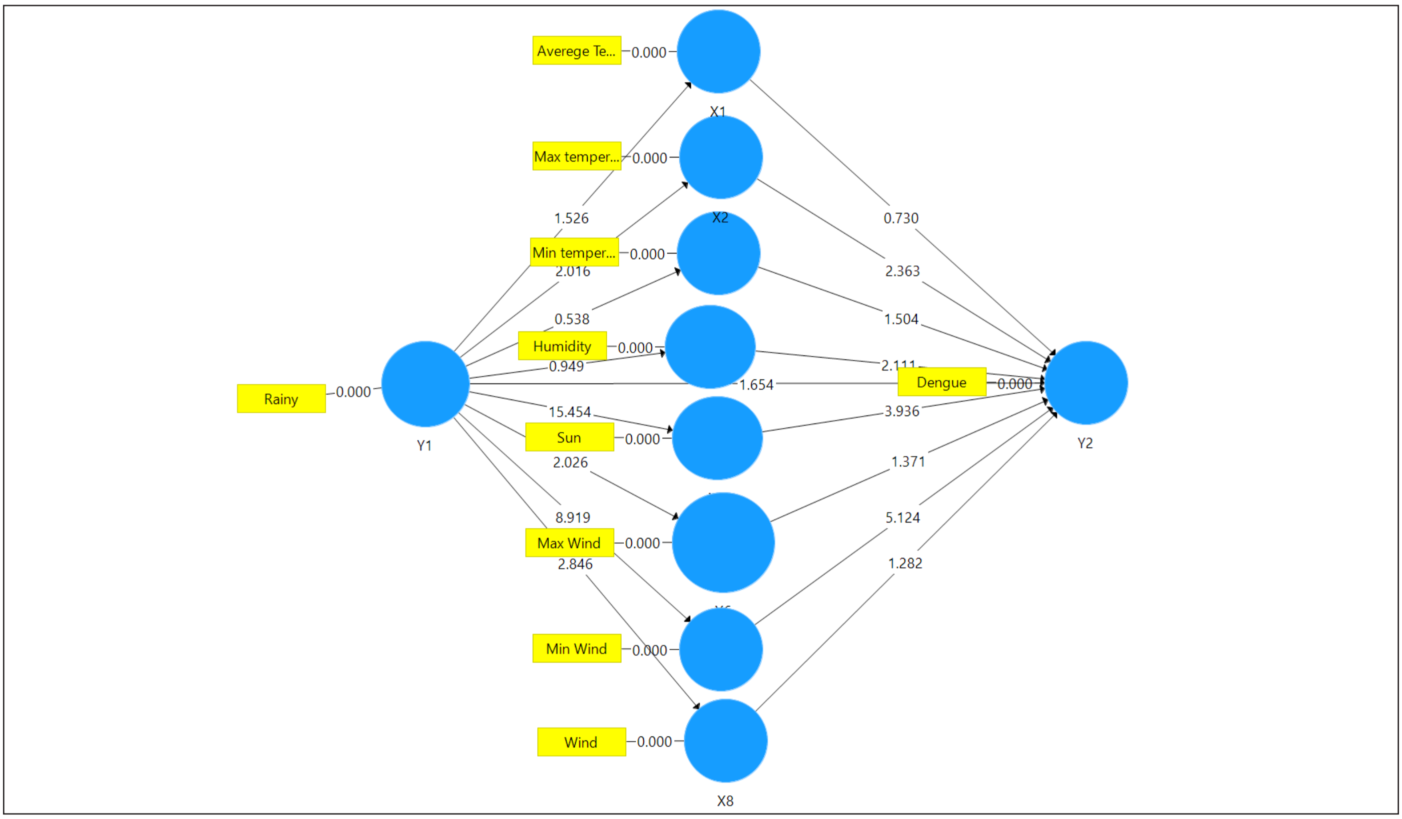

Figure 4. Path Analysis of Climate Factors with Dengue in Surabaya, Indonesia

Table 2. R² and Adjusted R² Values for Structural Equation Model of Climate-Dengue Relationship

	R Square	R Square Adjusted
X1	0.019	0.002
X2	0.070	0.054
X3	0.003	-0.014
X4	0.072	0.056
X5	0.562	0.555
X6	0.063	0.047
X7	0.463	0.454
X8	0.126	0.111
Y2	0.521	0.435

Table 2 shows that climate variables have varying contributions to the model, with sunlight (X5) having the highest R Square value of 0.562 (Adjusted $R^2 = 0.555$), followed by minimum wind speed (X7) of 0.463 (Adjusted $R^2 = 0.454$), indicating that these two factors are most strongly explained by other variables in the model, especially rainfall as the main determinant. In contrast, average temperature (X1), minimum temperature (X3), and maximum temperature (X2) show low R Square values (< 0.07), so their variations are relatively small influenced by rainfall. For the case of dengue (Y2), the R Square value of 0.521 with an Adjusted R Square of 0.435 indicates that approximately 52.1% of the variation in dengue cases in Surabaya can be explained by climate factors in the model, while the remainder is likely influenced by non-climatic factors such as community behavior, population density, environmental sanitation, and the effectiveness of vector control.

Table 3 presents the results of path analysis to test the direct influence of various variables on dengue fever cases (Y2) and the influence of rainfall (Y1) on several weather variables. The results show that of the eight variables tested, four of them have a statistically significant influence (p-value < 0.05) on Y2. These variables are Maximum Temperature (X2) which has a negative effect, Humidity (X4) and Sunlight (X5) which have a positive effect, and Minimum Wind Speed (X7) which also has a positive effect. On the other hand, rainfall (Y1) is only proven to significantly influence Maximum Temperature (X2) with a negative influence, while its influence on Average Temperature, Minimum Temperature, and Humidity is declared insignificant.

Table 3. The Relationship Predicting Climate and Dengue Case Factors

Correlation	Original Sample	Sample Mean	Standard Deviation	T Statistics	P-Value
X4 -> Y2	1,181	1,445	0.534	2,210	0.028*
X5 -> Y2	1,063	1,073	0.279	3,807	0.000*
X6 -> Y2	-0.556	-0.522	0.398	1,397	0.163
X7 -> Y2	0.777	0.731	0.161	4,840	0.000*
X8 -> Y2	0.480	0.577	0.364	1,318	0.188
Y1 -> X1	-0.136	-0.192	0.099	1,381	0.168
Y1 -> X2	-0.265	-0.285	0.133	1,996	0.046*
Y1 -> X3	0.056	0.044	0.102	0.549	0.583
Y1 -> X4	0.268	0.428	0.287	0.934	0.351
Y1 -> X5	-0.750	-0.759	0.046	16,191	0.000*
Y1 -> X6	-0.251	-0.254	0.126	1,984	0.048*
Y1 -> X7	0.681	0.682	0.072	9,515	0.000*
Y1 -> X8	-0.355	-0.358	0.121	2,938	0.003*
Y1 -> Y2	-0.351	-0.391	0.214	1,638	0.102

*Significant

DISCUSSION

Using a retrospective ecological design on monthly dengue case data from January 2020 to December 2024, this study demonstrates that the dynamics of dengue cases in Surabaya are influenced by a combination of climate factors through direct and indirect pathways. These findings confirm that dengue transmission in tropical urban environments is the result of complex interactions between climate variables that form an environmental system, rather than the sole influence of a single meteorological parameter.

Certain climate variables, maximum temperature, humidity, sunshine duration, and minimum wind speed, have a significant direct influence on dengue incidence. Several studies in Indonesia have shown that humidity, low wind speed, and air temperature are significantly associated with increased dengue fever cases (16–19). Rainfall acts as an indirect determinant that influences other climate variables, rather than as a direct predictor of dengue incidence (20). This indirect role indicates that rainfall acts as an upstream climatic driver that modifies urban microclimate conditions before impacting the risk of dengue transmission. Other studies have shown that, with a time-lagged effect, rainfall and temperature play a significant role in influencing dengue outbreaks (11).

Maximum temperatures are known to accelerate the life cycle of Aedes aegypti and dengue virus replication, but extreme temperatures can actually decrease mosquito survival (21). This relationship reflects the vector's threshold-dependent response to environmental temperature. Co-infection and warmer temperatures appear to promote faster dengue virus replication in the early stages of infection. One study showed that mosquito mortality rates were consistently lower at 32°C than at 27°C (22). The high relative humidity factor can increase the survival rate of adult mosquitoes and the opportunity for contact between vectors and humans (23). Humidity is a microclimatic factor that greatly influences the abundance of dengue fever vectors, but this study shows a negative correlation between the incidence of dengue fever and maximum humidity (24). These findings strengthen evidence that the influence of humidity is contextual and highly dependent on local environmental conditions and the dominant vector species. Furthermore, humidity factors show inconsistent correlations across mosquito species, so the direction of the relationship is not always the same (25).

The urban environment, particularly the duration of sunlight, influences micro-temperature and the availability of mosquito breeding habitats (26). The highest correlation value (r = 0.311) for the duration of sunlight variable indicates a positive association with increased dengue fever cases, as longer sunlight encourages mosquitoes to seek shaded resting places and tend to stay indoors (12). This phenomenon emphasizes the importance of urban microclimate factors, which are often overlooked in climate-based dengue risk modeling. Low maximum wind speeds allow for more stable mosquito flight activity and increase local transmission. Studies in Europe have shown that Aedes albopictus is not found under high maximum wind speeds, and each one-unit (m/s) increase in wind speed reduces the suitability of the vector's habitat by 3.16% (27). This suggests that wind dynamics serve as an important ecological constraint on the distribution and successful transmission of vectors.

The role of rainfall as an indirect factor, as demonstrated in this study, indicates that the relationship between rainfall and dengue fever is nonlinear. In a study using a distributed lag nonlinear model (DNLM), the cumulative exposure-response relationship between rainfall and dengue fever incidence showed a complex and spatially inconsistent pattern (5). Rainfall can influence dengue fever cases by modifying environmental conditions such as sunlight and wind speed. Consistent with research in Paraguay, rainfall and wind speed showed a negative association, while sunlight showed a positive association with dengue fever incidence (28). This finding conceptually challenges the linear assumption that increased rainfall is always synonymous with increased dengue risk.

In this study, the use of path analysis allows for the separation of direct and indirect influences that cannot be captured by conventional regression. This approach provides a systems-based analytical framework that is more suitable for examining the complex interactions of environmental factors. Path analysis separates correlations into direct and indirect effects of the explanatory variables on the primary variable (29). In addition, the integration of seasonal decomposition of time series reduces bias due to the recurring seasonal pattern of the dengue transmission cycle. This decomposition helps isolate long-term trends, seasonal variations, and residual fluctuations, thereby improving the interpretability of the climate-disease relationship (30). The R^2 value of 52.1% indicates that climatic factors have substantial explanatory power, although non-climatic factors still play a role. Other studies have also confirmed that climatic factors such as rainfall, humidity, temperature, wind speed, and sunshine duration contribute to the incidence of dengue fever (31). While population density and urban social characteristics also increase the risk of transmission (32).

The results of this study are in line with studies in Southeast Asia and Latin America which emphasize the role of temperature and humidity as the main determinants of dengue in tropical regions (33). Studies in South Asia also show that increasing temperature and relative humidity are associated with increased abundance of the Aedes vector (34). Variations in findings between regions reflect differences in environmental characteristics, levels of urbanization, and local climate dynamics. Continued urbanization in Central Africa, for example, has been associated with a 1.7% increase in Aedes aegypti abundance (35). Thus, this study enriches the global literature with empirical evidence from a coastal tropical metropolis that remains relatively underrepresented in dengue-climate studies.

Southeast and South Asia are expected to experience an increased risk of dengue transmission due to local climate change. Long-term mitigation efforts, such as limiting greenhouse gas emissions, have the potential to reduce the disease burden in the future (36). Climate variables such as temperature, rainfall, cloud cover, and surface pressure have been proposed as indicators in dengue early warning systems (37-38).

Studies in Southern Thailand have shown a strong association between climate indicators and dengue risk at the district level (39).The findings of this study support the development of an early warning system based on multiple climate indicators, rather than relying on a single variable such as rainfall. Integrating climate data with epidemiological surveillance also has the potential to increase the effectiveness of vector control interventions in urban areas. The climate-based risk index approach in Mexico demonstrated significant benefits in the context of regions with limited entomological capacity (40).

This study has several limitations. First, the ecological design does not allow for causal inference at the individual level. Second, non-climatic factors such as population mobility, community behavior, and vector control interventions have not been fully incorporated. In addition, part of the study period overlapped with the COVID-19 pandemic, which may have influenced dengue surveillance, healthcare-seeking behavior, and transmission dynamics. Nevertheless, the study utilized official dengue surveillance records from the Surabaya City Health Department, which remained operational throughout the pandemic period. Since the primary objective was to examine climate–dengue relationships rather than estimate absolute disease burden, the data were considered appropriate for the present analysis. However, the potential impact of pandemic-related behavioral and healthcare changes cannot be completely excluded. Third, the monthly resolution of the data may not capture weekly or daily dynamics. Fourth, this study focuses on the contemporary climate-dengue relationship and does not explicitly model lagged effects. Nevertheless, the systemic approach used provides a strong methodological foundation for further research. Future research is recommended to integrate high-resolution climate data, entomological data, and social factors using dynamic modeling or machine learning approaches and conduct cross-city studies to test the generalizability of the climate-dengue model.

CONCLUSION

This study demonstrates that dengue dynamics in Surabaya, a tropical coastal megacity, are governed by interconnected climatic pathways rather than isolated meteorological variables. Through a retrospective ecological design integrating seasonal time-series decomposition and path analysis, we show that maximum temperature, relative humidity, sunlight duration, and minimum wind speed exert significant direct effects on dengue incidence, while rainfall primarily functions as an indirect upstream driver by shaping urban microclimatic conditions. These findings highlight the non-linear and mediated nature of climate–dengue relationships and challenge conventional approaches that treat rainfall as a standalone predictor of dengue outbreaks in tropical urban environments.

By advancing a systems-based environmental epidemiology framework, this study provides novel empirical evidence from an underrepresented tropical metropolitan context and offers a transferable analytical approach for climate-sensitive disease research. The results underscore the need for dengue early warning systems and adaptive vector control strategies to incorporate multiple interacting climatic indicators, particularly those reflecting urban microclimate dynamics, under increasing climate variability and urbanization. As climate change continues to reshape environmental conditions in tropical cities, understanding climate-mediated dengue pathways is essential for strengthening urban health resilience and informing evidence-based public health interventions.

ACKNOWLEDGMENTS

The authors would like to express their sincere appreciation to the Surabaya City Health Department for providing access to dengue epidemiological data used in this study. We also gratefully acknowledge the Meteorological, Climatological, and Geophysical Agency of Indonesia (BMKG), particularly the Surabaya Station, for supplying the climate data and for making additional data publicly accessible through their official data portal.

AUTHORS' CONTRIBUTION

KCD: Conceptualization, Methodology, Data curation, Writing- Original draft preparation. RY: Supervision, Validation, Writing- Reviewing and Editing. LS: Investigation, Data curation, Writing- Reviewing and Editing. M: Data curation, Formal analysis. HA: Investigation, Validation. HBN: Formal analysis, Methodology. RD: Software, Visualization. FS: Data curation, Investigation. MRR: Resources, Data curation. BJ: Writing- Reviewing and Editing, Validation. ASP: Visualization, Writing- Reviewing and Editing. DAS: Investigation, Data curation, Writing- Reviewing and Editing. NI: Validation, Resources, Writing- Reviewing and Editing.

REFERENCES

1. Mahmood K, Rashid M, Ansari SK, Kanani F, Iftner T. Clinical Characteristics of Dengue Virus Infections in Karachi from 2019 to 2023: A Cross-Sectional Study. *Sci Rep*. 2024;14(31910):1–10. https://doi.org/10.1038/s41598-024-83425-0

2. World Health Organization. Dengue. Geneva: World Health Organization; 2025. https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue
3. Mamenun, Koesmaryono Y, Sopaheluwakan A, Hidayati R, Dasanto BD, Aryati R. Spatiotemporal Characterization of Dengue Incidence and Its Correlation to Climate Parameters in Indonesia. *Insects*. 2024;15(366):1–15. https://doi.org/10.3390/insects15050366
4. Permatasari WSR, Masjud YI. Impacts of Climate Variability on Mosquito-Borne Diseases : A Focus on Dengue Fever in Disaster Management and Community Resilience Perspectives. *JDMCR J Disaster Manag Community Resil*. 2024;1(1):1–8. https://doi.org/10.61511/jdmcr.v1i1.763
5. Polrob W, La-up A. 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*. 2025;25(4024):1–15. https://doi.org/10.1186/s12889-025-25420-2
6. Tian Y, Xu Y, Liang Y, Zhou Z, Susong KM, Chen Y, et al. Rising Dengue Risk with Increasing El Niño–Southern Oscillation Amplitude and Teleconnections. *Nat Commun*. 2025;16(8629):1–13. https://doi.org/10.1038/s41467-025-63655-0
7. Wiyono L, Rocha ICN, Cedeño TDD, Miranda AV, Iii DEL. Dengue and COVID-19 Infections in the ASEAN Region: A Concurrent Outbreak of Viral Diseases. *Epidemiol Health*. 2019;43(e2021070):1–5. https://doi.org/10.4178/epih.e2021070
8. Maramis A, Wispriyono B. Vulnerability Mapping of Dengue Hemorrhagic Fever (DHF) Cases in West Java Province in 2023. *Indones J Glob Heal Res*. 2025;7(5):295–306. https://doi.org/10.37287/ijghr.v7i5.6720
9. Ghaisani NP, Sulistiawati, Lusida MLI. Correlation between Climate Factors with Dengue Hemorrhagic Fever Cases in Surabaya 2007 – 2017 DHF Cases Profile in Surabaya. *Indones J Trop Infect Dis*. 2021;9(1):39–44. https://doi.org/10.20473/ijtid.v9i1.16075
10. Akbar H, Fikri D, Carles C, Usa WYM, Natsir RM, Pratama R, et al. The Effect of Climate Variability on Dengue Disease in Endemic Areas: A Study of Bandung City, Indonesia. *J Public Heal Dev*. 2025;23(3):276–291. https://doi.org/10.55131/jphd/2025/230321
11. Alam KE, Ahmed MJ, Chalise R, Rahman MA, Mathin TT, Bhuiyan MIH, et al. Time Series Analysis of Dengue Incidence and Its Association with Meteorological Risk Factors in Bangladesh. *PLoS One*. 2025;20(8):1–23. https://doi.org/10.1371/journal.pone.0323238
12. Larasati N, Basra MU. Faktor Iklim Berdasarkan Lag Time yang Berhubungan dengan Kasus DBD di Kabupaten Pesisir Selatan Climate Factors Based on Lag Time Associated with DHF Cases in Pesisir Selatan Regency. *JIK (Jurnal Ilmu Kesehatan)*. 2025;9(1):9–18. https://doi.org/10.33757/jik.v9i1.1138
13. Patil S, Pandya S. Forecasting Dengue Hotspots Associated with Variation in Meteorological Parameters Using Regression and Time Series Models. *Front Public Heal*. 2021;9(798034):1–16. https://doi.org/10.3389/fpubh.2021.798034
14. Polwiang S. The Time Series Seasonal Patterns of Dengue Fever and Associated Weather Variables in Bangkok (2003-2017). *BMC Infect Dis*. 2020;20(208):1–10. https://doi.org/10.1186/s12879-020-4902-6
15. Tang SCN, Rusli M, Lestari P. Climate Variability and Dengue Hemorrhagic Fever in Surabaya , East Java , Indonesia. *Indian J Public Heal Res Dev*. 2020;11(2):131–137. https://doi.org/10.37506/v11/i2/2020/ijphrd/194770
16. Sapta WA, Rosita Y, Astuti M. Hubungan Faktor Iklim Terhadap Kejadian Demam Berdarah Dengue (DBD) di Kabupaten Lampung Barat Tahun 2022-2024. *J Kesehat Tambusai*. 2025;6(3):13072–13081. https://doi.org/10.31004/jkt.v6i3.46984
17. Arieskha FTA, Rahardjo M, Joko T. The Association between Weather Variability and Dengue Hemorrhagic Fever in Tegal Regency. *J Kesehat Lingkung*. 2019;11(4):339–347. https://doi.org/10.20473/jkl.v11i4.2019.339-347
18. Sutriyawan A, Kurniati N, Novianti N, Farida U, Yusanti L, Destriani SN, et al. Analysis of Temperature, Humidity, Rainfall, and Wind Velocity on Dengue Hemorrhagic Fever in Bandung Municipality. *Russ J Infect Immun*. 2024;14(1):155–162. http://dx.doi.org/10.15789/2220-7619-AOT-2110
19. Ulya ID, Kesetyaningsih TW. The Relationship between Climate Factors and the Incidence of Dengue Hemorrhagic Fever in Sumenep Regency, East Java. *Proceedings The 3rd UMY Grace 2022*. 2022; 207–212. https://prosiding.umy.ac.id/grace/index.php/pgrace/article/download/432/394
20. Cruz EI, Salazar F V, Aguila AMA, Villaruel-jagmis MV, Ramos J, Paul RE. Current and Lagged Associations of Meteorological Variables and Aedes mosquito Indices with Dengue Incidence in the Philippines. *PLoS Negl Trop Dis*. 2024;18(7):1–23. http://dx.doi.org/10.1371/journal.pntd.0011603
21. Abbasi E. The Impact of Climate Change on Aedes aegypti Distribution and Dengue Fever Prevalence in Semi-arid Regions: A case study of Tehran Province, Iran. *Environ Res*. 2025;275(121441):1–8. https://doi.org/10.1016/j.envres.2025.121441
22. Terradas G, Manzano-Alvarez J, Vanalli C, Werling K, Cattadori IM, Rasgon JL. Temperature Affects Viral Kinetics and Vectorial Capacity of Aedes aegypti Mosquitoes Co-infected with Mayaro and Dengue Viruses. *Parasit Vectors*. 2024;17(73):1–13. https://doi.org/10.1186/s13071-023-06109-0
23. Yani A. The Influence of Environmental Factors on the Development of Dengue Fever. *Int Sci Heal J*. 2024;2(4):116–123. https://doi.org/10.59680/ishel.v2i4.1569
24. Faridah L, Fauziah N, Agustian D, Jaya IGNM, Putra RE, Watanabe K, et al. Temporal Correlation Between Urban Microclimate, Vector Mosquito

Abundance, and Dengue Cases. *J Med Entomol*. 2022;59(3):1008–1018. https://doi.org/10.1093/jme/tjac005

25. Dom NC, Abdullah NAMH, Dapari R, Salleh SA. Fine-scale Predictive Modeling of Aedes mosquito Abundance and Dengue Risk Indicators Using Machine Learning Algorithms with Microclimatic Variables. *Sci Rep*. 2025;15(37017):1–10. https://doi.org/10.1038/s41598-025-17191-y
26. Sureshkumar S, Shekhar S. Impact of Urban Heat Island Effect on Dengue Incidence: A Remote Sensing Approach Using Thermal and High-resolution Optical Imagery. *BMC Public Health*. 2025;25(2914):1–13. https://doi.org/10.1186/s12889-025-23763-4
27. Adeleke ED, Shittu RA, Beierkuhnlein C, Thomas SM. High Wind Speed Prevents the Establishment of the Disease Vector Mosquito Aedes albopictus in Its Climatic Niche in Europe. *Front Environ Sci*. 2022;10(846243):1–13. https://doi.org/10.3389/fenvs.2022.846243
28. Gómez REG, Kim J, Kim J, Jang JY, Kisiju T, Kim S, et al. Association between Climate Factors and Dengue Fever in Asuncion, Paraguay: A Generalized Additive Model. *Int J Environ Res Public Heal Artic*. 2022;19(12192):1–10. https://doi.org/10.3390/ijerph191912192
29. Senhorelo AP, Sousa EF de, Santos AR dos, Ferrari JL, Peluzio JBE, Carvalho R de CF, et al. Application of Path Analysis and Remote Sensing to Assess the Interrelationships between Meteorological Variables and Vegetation Indices in the State of Espírito Santo, Southeastern Brazil. *Diversity*. 2024;16(90):1–24. https://doi.org/10.3390/d16020090
30. Das P, Barman S. Perspective Chapter: An Overview of Time Series Decomposition and Its Applications. *In Applied and Theoretical Econometrics*. 2025; 1–15. https://doi.org/10.5772/intechopen.1009268
31. Cahyati WH, Marpid AD, Nugroho E, Suharyo S. Climate Factors with the Incidence of Dengue Hemorrhagic Fever in Semarang, Indonesia. *Kemas J Kesehat Masy*. 2024;20(2):339–346. https://journal.unnes.ac.id/nju/kemas/article/download/50328/15908
32. Amelinda YS, Wulandari RA, Asyary A. The Effects of Climate Factors, Population Density, and Vector Density on the Incidence of Dengue Hemorrhagic Fever in South Jakarta Administrative City 2016–2020: An Ecological Study. *Acta Biomed*. 2022;93(6):1–10. https://doi.org/10.23750/abm.v93i6.13503
33. Garcıa YE, Chou-Chen SW, Barboza LA, Daza–Torres ML, Montesinos-Lopez JC, Vasquez P, et al. Common Patterns between Dengue Cases, Climate, and Local Environmental Variables in Costa Rica: A Wavelet Approach. *Plos Glob Public Heal*. 2023;3(10):1–22. https://doi.org/10.1371/journal.pgph.0002417
34. Islam S, Haque CE, Hossain S, Hanesiak J. Climate Variability, Dengue Vector Abundance and Dengue Fever Cases in Dhaka, Bangladesh: A Time-Series Study. *Atmosphere (Basel)*. 2021;12(905):1–21. https://doi.org/10.3390/atmos12070905
35. Montgomery MJ, Harwood JF, Yougang AP, Wilson-Bahun TA, Tedjou AN, Keumeni CR, et al. The Effects of Urbanization, Temperature, and Rainfall on Aedes aegypti and Aedes albopictus Mosquito Abundance Across a Broad Latitudinal Gradient in Central Africa. *Parasit Vectors*. 2025;18(135):1–11. https://doi.org/10.1186/s13071-025-06764-5
36. Wang Y, Zhao S, Wei Y, Li K, Jiang X, Li C, et al. Impact of Climate Change on Dengue Fever Epidemics in South and Southeast Asian settings : A Modelling Study. *Infect Dis Model*. 2023;8(3):645–655. https://doi.org/10.1016/j.idm.2023.05.008
37. Leung XY, Islam RM, Adhami M, Ilic D, Mcdonald L, Palawaththa S, et al. A Systematic Review of Dengue Outbreak Prediction Models: Current Scenario and Future Directions. *PLoS Negl Trop Dis*. 2023;17(2):1–21. http://dx.doi.org/10.1371/journal.pntd.0010631
38. Sugeno M, Kawazu EC, Kim H, Banouvong V, Pehlivan N, Gilfillan D, et al. Association Between Environmental Factors and Dengue Incidence in Lao People's Democratic Republic: A Nationwide Time-series Study. *BMC Public Health*. 2023;23(2348):1–10. https://doi.org/10.1186/s12889-023-17277-0
39. Abdulsalam FI, Antunez P, Yimthiang S, Jawjit W. Influence of Climate Variables on Dengue Fever Occurrence in the Southern Region of Thailand. *Plos Glob Public Heal*. 2022;2(4):1–17. https://doi.org/10.5772/intechopen.1009268
40. Carreto C, Gutiérrez-Romero R, Rodríguez T. Climate-driven Mosquito-borne Viral Suitability Index : Measuring Risk Transmission of Dengue, Chikungunya and Zika in Mexico. *Int J Health Geogr*. 2022;21(15):1–23. https://doi.org/10.1186/s12942-022-00317-0