Journal of Epidemiology and Public Health (2026), 11(03): 271-283
Master's Program in Public Health, Universitas Sebelas Maret

Original Research
Open Access

Scalable Forecasting Geoanalytics for Epidemic Dengue Risk in East Java

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Received: April 04, 2026; Accepted: June 29, 2026; Available online: July 16, 2026

ABSTRACT

Background: Current methods for managing Dengue Hemorrhagic Fever (DHF) in East Java often separate temporal and spatial analyses, hindering proactive public health interventions. To address this limitation, this study develops an integrated spatio-temporal framework that combines multi-model forecasting and geospatial analysis to create localized dengue projections and risk maps.

Subjects and Method: An ecological spatio-temporal design was conducted across 38 districts/ cities in East Java using secondary data from 2013–2023. The dependent variable was annual dengue incidence, while independent variables comprised natural factors (e.g., rainfall, humidity) and social factors (e.g., population density, poverty). Data were analyzed using Geographically Weighted Regression (GWR) for spatial modeling. Time series forecasting for the 2024–2028 period was conducted using Trigonometric seasonality, Box-Cox transformation (TBATS), Auto-regressive Integrated Moving Average (ARIMA), Prophet, and Neural NETwork AutoRegression (NNETAR) models, evaluated by Root Mean Square Error (RMSE).

Results: Rainfall demonstrated the strongest natural association (R^2=0.49; p=0.022), followed by humidity (R^2=0.26; p<0.001). Epidemiologically, population density emerged as the key social determinant (R^2=0.50; p=0.005). TBATS achieved the highest forecasting accuracy with the lowest RMSE (47.657), outperforming ARIMA (202.980), Prophet (172.809), and NNETAR (157.653). Spatial risk mapping revealed that high-risk social clusters are heavily concentrated in the eastern 'Tapal Kuda' region and northern coastal metropolitan corridors.

Conclusion: Dengue incidence in East Java is significantly driven by climatic factors and spatially varying social vulnerabilities. The integration of TBATS forecasting and GWR spatial modeling provides a robust framework for anticipating future case burdens and identifying priority intervention areas, thereby supporting highly targeted public health planning.

Keywords: dengue; forecasting; spatial analysis, population density

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Cite this as:
Supriyanto BF, Nurjihan I, Putri NAM, Tursina E, Suhartini AM (2026). Scalable Forecasting Geoanalytics for Epidemic Dengue Risk in East Java. *J Epidemiol Public Health*. 11(3): 271-283. https://doi.org/10.26911/je-publichealth.2026.11.03.05.

BACKGROUND

Dengue Hemorrhagic Fever (DHF) remains a major endemic infectious disease characterized by recurrent seasonal surges, particularly in tropical regions such as Indonesia (Riaz et al., 2024). In East Java Province, the spatial and temporal distribution of dengue cases varies considerably across districts and cities, indicating heterogeneous transmission dynamics (Parveen et al., 2023). These variations are influenced by a combination of natural and social determinants. Natural factors such as rainfall, temperature, and seasonal variability have long been recognized as key drivers of dengue transmission through their effects on mosquito breeding and viral replication(Cunha et al., 2022). Meanwhile, social factors including population density, settlement characteristics, and sanitation behavior play a critical role in shaping human vector interactions and local transmission intensity(Sudarmaja et al., 2022).

From a public health policy perspective, the ability to anticipate dengue case surges is essential for effective planning and resource allocation. Accurate projections enable local governments to prepare logistics such as insecticides, laboratory reagents, hospital bed capacity, and healthcare workforce readiness. However, in many cases, policy responses remain reactive due to the lack of integrated and predictive analytical frameworks (Gupta et al., 2023). This reactive approach often limits the effectiveness of interventions and increases the burden on healthcare systems. Therefore, there is a pressing need for evidence-based tools that can provide both temporal projections and spatial prioritization to support proactive decision-making.

Previous studies in Indonesia have predominantly focused on climate-based determinants of dengue transmission, often analyzing variables such as rainfall and temperature in isolation(Damtew et al., 2023). In contrast, social determinants, particularly population density, are less frequently examined as independent and spatially varying risk factors, despite evidence suggesting their significant contribution to local transmission heterogeneity (Faridah et al., 2022). Furthermore, methodological approaches tend to be fragmented. Time series forecasting models, such as Trigonometric seasonality, Box-Cox transformation (TBATS), Auto¬regressive Integrated Moving Average (ARIMA), Prophet, and Neural NETwork Auto-Regression (NNETAR) models, are widely used to predict future case trends based on historical data (Zhao & Zhang, 2022; Oh & Seong, 2024) (Perone, 2022). However, these models are typically applied without integration into spatial analytical frameworks. On the other hand, geospatial methods such as Geographically Weighted Regression (GWR) are effective in capturing spatial heterogeneity and local variations in relationships between variables (Yang et al., 2023), yet they are rarely combined with forecasting outputs.

This methodological separation creates a critical gap: while forecasting models can estimate the magnitude and timing of future cases, they do not indicate where interventions should be prioritized. Conversely, spatial models identify high-risk areas but lack forward-looking projections. As a result, the linkage between predicted case burden and geographically targeted intervention strategies remains weak (Na et al., 2023) . Addressing this gap requires an integrated analytical framework that combines temporal forecasting with spatial modeling to produce both predictive and location-specific insights.

This study integrates multiple time series forecasting models TBATS, ARIMA, Prophet, and NNETAR with spatial analysis using Geographically Weighted Regression (GWR). Each model contributes distinct analytical strengths: TBATS is capable of capturing complex seasonal patterns (Liu et al., 2023), ARIMA serves as a classical benchmark for time series modeling (Box and Jenkins, 1976), Prophet offers scalability and flexibility for large datasets (Taylor and Letham, 2018), and NNETAR introduces nonlinear pattern recognition through neural network approaches (Kontopoulou et al., 2023). The accuracy of these models is evaluated using Root Mean Square Error (RMSE), a widely accepted metric for forecast performance assessment (Wang & Gayed, 2026). Meanwhile, GWR is applied to examine the spatially varying relationship between dengue incidence and key social factors, particularly population density.

East Java Province was selected as the study area due to its distinct spatial and demographic heterogeneity, which provides an ideal dynamic for evaluating the Geographically Weighted Regression (GWR) model. Comprising 38 diverse districts and cities, the province exhibits a unique contrast between densely populated metropolitan hubs (such as Surabaya and Sidoarjo) and less populated rural or mountainous regions. This diversity enables a robust observation of the spatially varying relationships between social determinants and dengue transmission. Furthermore, as a region that consistently demonstrates a high and fluctuating endemic burden of dengue fever, East Java serves as a highly representative testbed for integrating scalable temporal forecasting with geospatial analytics.

Based on this framework, the research questions are formulated as follows: (1) What natural factors most influence the annual variation in dengue cases in East Java? (2) What are the most influential social factors? (3) How does the spatial relationship between dengue incidence and key social factors vary across districts/cities? and (4) How can dengue risk maps based on 2024–2028 forecasts be developed to identify priority intervention areas? Therefore, this study aimed to develop an integrated spatio-temporal analytical framework that combines multi-model time series forecasting and geospatial modeling to generate district/city-level dengue projections and risk maps in East Java, thereby supporting evidence-based and targeted public health interventions

SUBJECTS AND METHOD

1. Study Design

This study employed an ecological design with a spatio-temporal analytical approach. It integrates multi-model time series forecasting and geospatial modeling to examine dengue fever dynamics across districts/cities in East Java Province. Historical data from 2013 to 2023 were analyzed to identify patterns and generate projections for the 2024–2028 period.

2. Population and Sample

The population of this study comprised all districts and cities in East Java Province. A total of 38 districts/cities were included as the study sample using a total sampling approach, based on the availability and completeness of secondary data from the Central Bureau of Statistics (BPS). The unit of analysis in this study was the district/city-level, ensuring comparability across regions.

3. Study Variables

This study examined dengue fever incidence as the dependent variable, measured as the annual number of reported cases per district/city. The independent variables consisted of natural and social factors. Natural factors included rainfall, temperature, number of rainy days, humidity, air pressure, wind speed, and sunshine duration. Social factors included population density, number of working population, number of poor population, household sanitation conditions, and the number of criminal cases. In addition, spatial variables were incorporated in the form of district/ city administrative boundaries to support geospatial analysis.

4. Operational Definition of Variables

Dengue cases: Total reported annual dengue fever cases per district/city.

Population density: Number of people per square kilometer in each district/city.

Rainfall: Total annual rainfall (mm).

Temperature: Average annual temperature (°C).

Rainy days: Total number of rainy days per year.

Humidity: Average annual relative humidity (%).

Air pressure: Average annual atmospheric pressure (hPa).

Wind speed: Average annual wind speed (m/s).

Sunshine duration: Total annual duration of sunlight exposure.

Sanitation: The percentage of households with access to proper and improved sanitation facilities (e.g., private latrines with septic tanks) in a given year, as standardized by the Central Bureau of Statistics/ *Badan Pusat Statistik* (BPS).

Working population: The total number of individuals aged 15 years and over who are economically active and currently employed.

Poor population: The total number of individuals living below the official regional poverty line.

Criminal offenses: The total number of reported criminal cases (crime total) within a district/city per year. In this study, it serves as a proxy indicator for social dynamics, rapid urbanization, and settlement density.

Socioeconomic variables: Number of the working population, the poor population, and criminal cases.

5. Study Instruments

This study utilized secondary data obtained from official databases, primarily from the Central Bureau of Statistics (BPS). Data processing and analysis were conducted using RStudio for statistical analysis and time series forecasting, while QGIS was used for spatial visualization and map generation. These tools enabled the integration of temporal and spatial data into a unified analytical framework.

6. Data analysis

The analysis was conducted through several sequential stages. First, data preprocessing was performed, including cleaning, standardizing regional names, removing duplicates, and ensuring consistency across datasets. Second, an exploratory bivariate analysis was conducted using Pearson correlation represented by the Coefficient of Determination (R^2) derived from simple linear regression to assess the initial relationship between dengue cases and each independent variable. The Pearson method was selected because both the dependent and independent variables are continuous in nature, allowing for a standard and robust measurement of their linear association. This was subsequently visualized using thematic maps. Third, time series forecasting was conducted using four candidate models: TBATS, ARIMA, Prophet, and NNETAR. Model performance was evaluated using Root Mean Square Error (RMSE), and the model with the lowest RMSE value was selected for projecting dengue cases for the period 2024–2028. Fourth, spatial analysis was performed using correlation mapping and Geographically Weighted Regression (GWR) to capture spatial heterogeneity and estimate local relationships between dengue cases and population density. Band-width selection in the GWR model was conducted automatically using the Akaike Information Criterion corrected (AICc). Finally, the outputs were generated in the form of projection tables, time series graphs, and thematic maps, including five-year average projection maps, correlation maps, and spatial coefficient maps to support decision-making.

To ensure the validity of the models, rigorous assumptions and diagnostic tests were applied. For the time series forecast-ing, the Augmented Dickey-Fuller (ADF) test was utilized to evaluate data statio-narity prior to modeling. Post-modeling diagnostics included the Ljung-Box test to confirm that the residuals of the selected models resembled white noise, indicating no significant autocorrelation. For the spatial analysis, the Variance Inflation Factor (VIF) was calculated to check for multicollinearity among the independent variables before executing the GWR model, ensuring that only distinct predictors were included. Furthermore, Moran's I test was applied to the GWR residuals to verify that spatial autocorrelation was adequately resolved by the local model.

7. Research Ethics

This study used secondary data aggregated at the district/city level obtained from publicly accessible sources. Since no individual-level or identifiable personal data were involved, ethical approval was not required. However, all data were managed and analyzed in accordance with applicable data use and research integrity standards.

RESULTS

1. Association between Natural Factors and Dengue Cases

Descriptive statistics of the variables used in this study across the 38 districts and cities in East Java. Due to the varying availability of historical secondary data, baseline data from specific representative years were utilized for the social factors: population density reflects the 2023 demographic data, while criminal offenses are based on the 2017 official records. Show on table 1.

Table 1. Descriptive Statistics of Study Variables

Variables	Minimum	Maximum	Mean	SD
Natural Factors				
Rainfall (mm)	0	886	171.37	169.58
Humidity (%)	55	84	72.33	5.96
Sunshine Duration	4	99	64.97	25.73
Social Factors				
Population Density (per km^2)	410	8667	1938	2279
Criminal Offenses	75	779	428.56	157,09

To further evaluate the spatially varying impact of population density on dengue cases across the province, a Geographically Weighted Regression (GWR) model was applied. Unlike traditional global regression models that assume uniform relationships across the entire study area, GWR accounts for spatial heterogeneity by generating distinct local coefficients for each district and city. The distribution of these local estimates, along with key diag-nostic parameters indicating the model's performance and spatial fit, are summarized in Table 2.

Table 2. GWR Local Coefficients Summary and Model Diagnostics

Parameter	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Intercept	238.93	250.70	274.74	309.05	332.10
Population Density Coefficient	-0.03	-0.02	-0.02	-0.02	-0.02

Model Diagnostics:
Adaptive Bandwidth (Quantile): 0.571 (encompassing approximately 19 out of 35 observed data points)
Residual Sum of Squares (RSS): 1,146,781
AICc (GWR): 472.558
Quasi-global R-squared: 0.161

Table 3 presents the coefficient of determination (R^2) and the statistical significance (p-value) for various natural factors. Based on the analysis, rainfall shows the strongest relationship with the dependent variable, accounting for 49% of the variance (R^2= 0.49) (p = 0.022). Furthermore, humidity and sunshine also have significant correlations, with p <0.001 (R^2 = 0.26) and 0.004 (R^2 = 0.15), respectively. Conversely, the model indicates that air pressure (p= 0.460), wind speed (p=0.465), and rainy days (p= 0.355) do not have a statistically significant relationship, as their p-values exceed the standard 0.05 significance threshold.

Table 3. R^2 Values of Natural Factors

Natural Factors	R^2	p
Humidity	0.26	<0.001
Air Pressure	0.19	0.460
Wind Speed	0.18	0.465
Sunshine	0.15	0.004
Rainfall	0.49	0.022
Rainy Days	0.08	0.355

2. Association between Social Factors and Dengue Cases

Table 4 presents the relationship between social factors and dengue incidence. Criminal offenses showed the highest association (R^2 = 0.70; p = 0.026), followed by population density (R^2= 0.50; p= 0.005) and the number of working population (R^2= 0.50; p<0.001). Household sanitation (R^2 = 0.40; p = 0.044) and the number of poor population (R^2 = 0.33; p = 0.019) also demonstrated statistically significant relationships. Despite the highest R^2 observed for criminal offenses, population density was prioritized for further spatial modeling due to stronger epidemiological relevance.

Table 4. R^2 Values of Social Factors

Social Factors	R^2	p
Population Density	0.50	0.005
Working Population	0.50	<0.001
Poor Population	0.33	0.019
Sanitation	0.40	0.044
Criminal Offenses	0.70	0.026

3. Forecasting Model Performance

The comparison of forecasting models using RMSE is presented in Table 5. The TBATS model achieved the lowest RMSE (47.66), indicating the highest prediction accuracy, followed by NNETAR (157.65), Prophet (172,81), and ARIMA (202.98).

Table 5. Comparison Model Performance

Model	RMSE
Prophet	172.81
TBATS	47.66
ARIMA	202.98
NNETAR	157.65

4. Dengue Forecast Projection (2024-2028)

The bar chart in Figure 1 shows the forecasting results using the TBATS model, which was performed on historical data from 2024 to 2028 for each regency/city in East Java. It can be seen that there is a generally stable pattern between years (gradual increase/decrease without sharp spikes). In some regions, consistently high scores can be achieved, including Jember, Malang, Kediri, Sidoarjo, and Pacitan. Meanwhile, other cities/districts are at a lower level, such as Bangkalan, Batu City, and Probolinggo City, Indonesia.

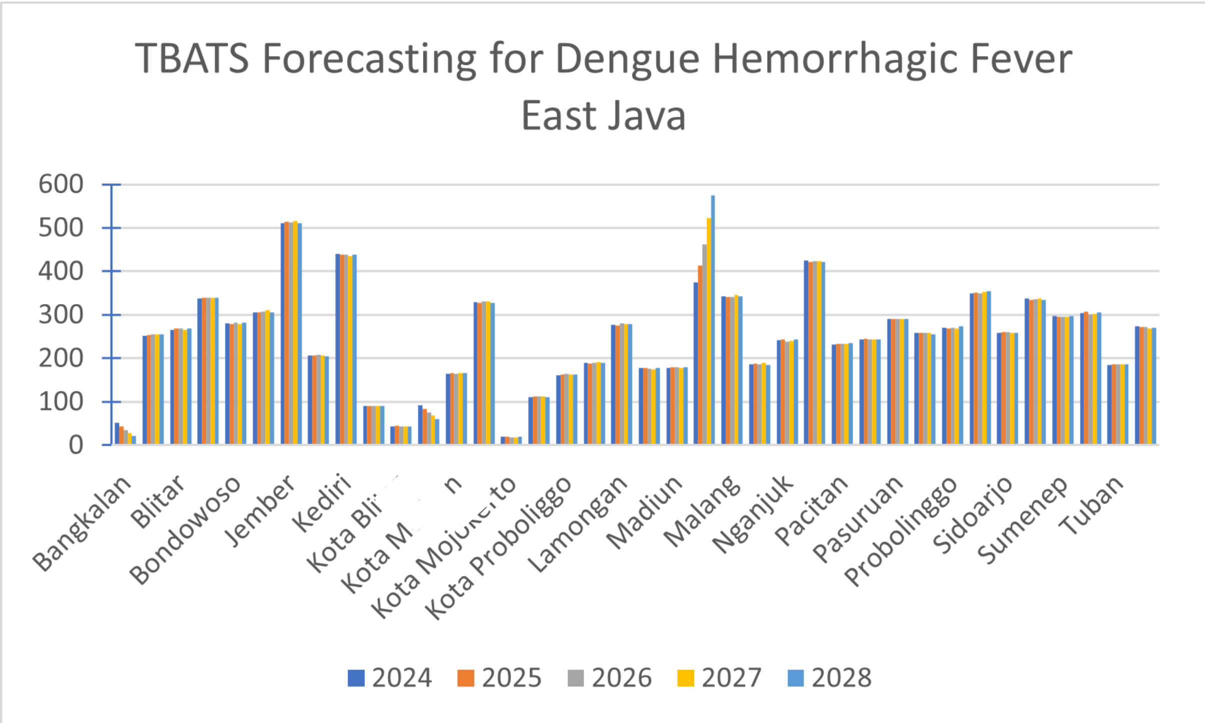

Figure 1. Forecasting Results Diagram with the TBATS Model

The map in Figure 2 shows the average forecasting results using the TBATS model for the five years from 2024 to 2028, broken down by administrative division (regency/city) in East Java. The values in the legend are divided into six classes based on their range, namely 20–164; 164–195; 195–259; 259–288; 288–339; 339–513, making the differences in the projected average cases on the map easy to read and distinguish between regions. Classes in the legend help interpret forecasting results as one of the supporting factors in decision-making, such as stock planning in the healthcare sector, scheduling control activities, service capacity management, and the provision of SMA from 2024 to 2028.

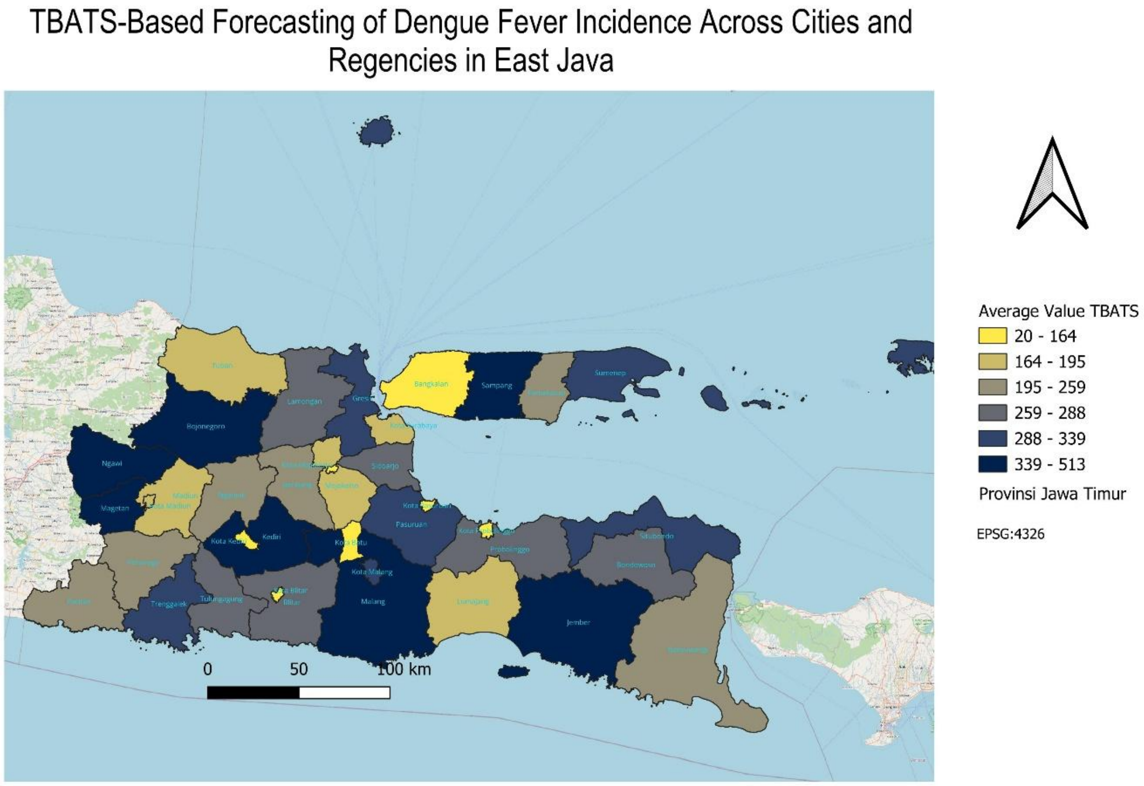

Figure 2. Map TBATS-Based Forecasting

Overall, there appears to be an uneven distribution of burden: several districts/ cities fall into the high category (≥339), while others are in the low-medium category. Referring to the same projection data, examples of regions with high values include Jember, Kediri, Ngawi, Magetan, Sampang, Malang, Situbondo, and Bojonegoro, making them worthy of priority in logistics planning and service capacity. Conversely, areas with low values, such as Bangkalan or Batu City, do not mean they are neglecting healthcare planning, but vigilance is still necessary, with strategies focused on maintaining achievements and strengthening surveillance.

5. Spatial Patterns of Social Risk

Figure 3 shows a social risk map calculated from the correlation (R-value) between dengue fever cases and population density at the district/city level in East Java. The R-values are mapped into five classes from -1 to 1: light colors indicate negative/weak correlation, while darker colors indicate strong positive correlation (approaching 1). This map visualization is used to see in which regions density is more related to variations in dengue fever cases, considering that population density is an epidemiologically relevant social factor in the urban tropical context.

Distinct spatial clustering of social factor-based dengue risk across East Java. Rather than a random distribution, the map reveals a strong geographical divide. The highest risk values (ranging from 0.6 to 1, depicted in the darkest shade) are heavily concentrated in the eastern and south-eastern parts of the province, often referred to as the 'Tapal Kuda' (Horseshoe) region (e.g., Banyuwangi, Jember, Situbondo, Bondowoso, Probolinggo), extending along the northern coastal metropolitan corridor up to Pasuruan, Sidoarjo, and Surabaya. Additionally, high-risk clusters are observed in parts of Madura Island (Sampang and Pamekasan) and the southwestern tip (Pacitan).

In contrast, regions with the lowest social risk values (-1 to -0.6) are predominantly clustered in the central and western inland areas (such as Ngawi, Bojonegoro, Nganjuk, Jombang, and Malang). This observed spatial pattern suggests that high social risk for dengue is strongly associated with coastal, highly urbanized, and densely populated corridors, as well as specific socio-cultural zones in the eastern region, whereas inland agricultural districts tend to exhibit lower social vulnerability to the disease.

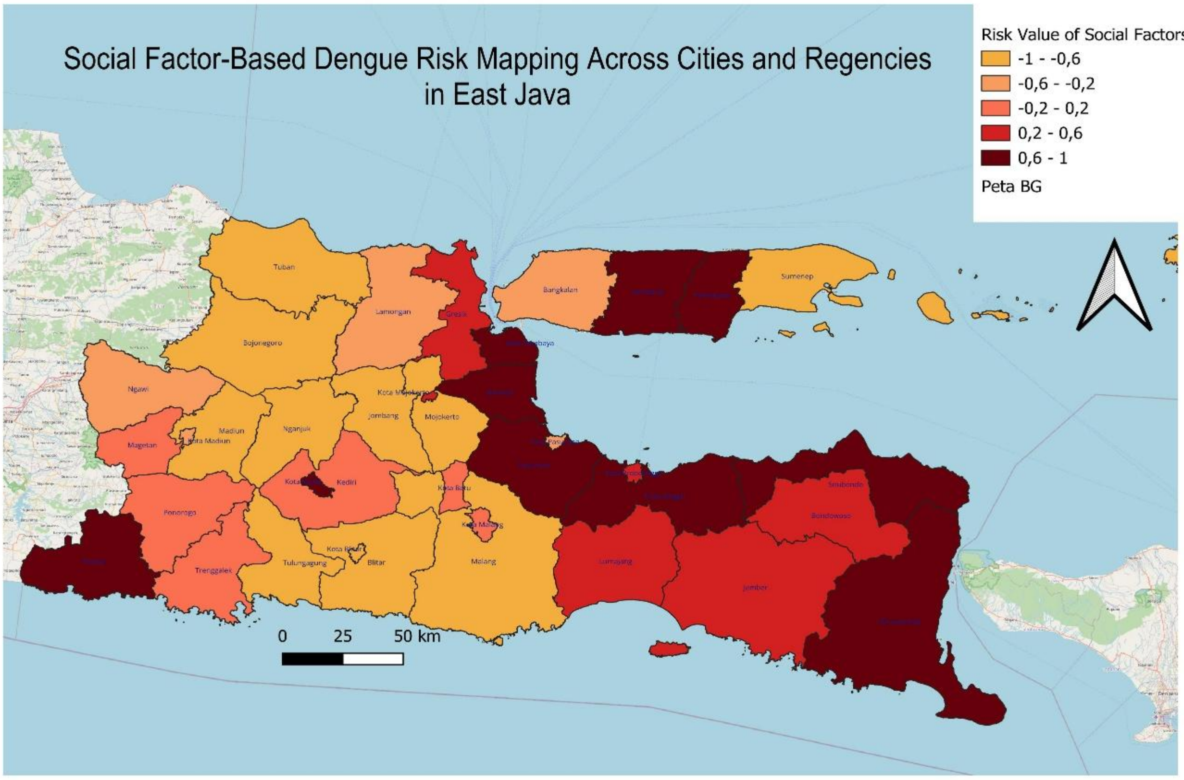

Figure 3. Map Social Factor Risk of Dengue Risk in East Java, Indonesia

The correlation map between dengue cases and population density reveals spatial heterogeneity in social risk. Strong positive correlations were observed in urban and densely populated areas, including Surabaya, Sidoarjo, Gresik, and regions in Madura Island. Similarly, high correlations were found in the Tapal Kuda region. Conversely, weaker correlations were identified in western and mountainous areas, suggesting that other determinants, such as environmental and behavioral factors, may play a more dominant role in these regions.

DISCUSSION

This study demonstrates that dengue transmission in East Java is influenced by both environmental and social determinants, with rainfall emerging as the most influential natural factor. This finding is consistent with previous studies showing that increased rainfall enhances mosquito breeding habitats and accelerates dengue transmission cycles (Morin et al., 2013). Humidity and sunshine also contributed significantly, reflecting the importance of climatic suitability in vector survival and viral replication. Based on the social perspective, population density was identified as a key determinant of dengue incidence. Although criminal offenses showed the highest statistical association, this variable likely acts as a proxy for urbanization rather than a direct causal factor. Population density, on the other hand, has a clear biological and epidemiological basis, as higher density increases human vector contact rates and facilitates virus transmission (de Souza & Weaver, 2024). This supports previous findings that urban and peri-urban areas are hotspots for dengue transmission in tropical settings.

The superiority of the TBATS model in forecasting performance aligns with its ability to capture complex seasonal and multi-seasonal patterns, which are characteristic of infectious diseases such as dengue (Abbasi, 2025) .Compared to classical models such as ARIMA, TBATS provides greater flexibility in handling non-linear and recurring seasonal structures, resulting in significantly lower prediction error. The use of RMSE as an evaluation metric further strengthens the reliability of model selection, as it is sensitive to large deviations and widely used in forecasting studies (Li et al., 2024).

The integration of forecasting outputs with spatial analysis represents a key contribution of this study. While previous research often treats forecasting and spatial modeling separately, this study demonstrates the added value of combining both approaches. Forecasting provides insights into the magnitude and timing of future cases, whereas spatial analysis—particularly using Geographically Weighted Regression (GWR) reveals local variations in risk factors. This combination enables more targeted and efficient intervention planning, bridging the gap between “how many cases will occur” and “where interventions should be prioritized” (Chen et al., 2022 ;Fotheringham et al., 2022;H. Wang et al., 2026).

The spatial findings highlight that the influence of population density is not uniform across regions. Stronger effects were observed in urban and densely populated corridors, while weaker associations were found in rural or mountainous areas. This indicates that dengue transmission is context-specific, and intervention strategies should be tailored accordingly. In high-density areas, vector control and environmental management should be intensified, while in low-density areas, focus may shift toward surveillance and community-based prevention.

Based on a policy perspective, the relatively stable projection of dengue cases suggests a persistent endemic burden in East Java. This underscores the need for continous preparedness rather than seasonal reactive responses. The five-year projection can serve as a basis for logistics planning, healthcare capacity management, and scheduling of vector control programs. Meanwhile, spatial risk maps can guide the prioritization of high-risk districts, ensuring more efficient allocation of resources.

However, this study has several limitations. First, the use of annual aggregated data may mask short-term fluctuations and seasonal peaks, which are important in dengue epidemiology. Second, the spatial model primarily focuses on population density as a social determinant, while other potential factors, such as mobility, behavior, and environmental conditions, were not fully incorporated. Future research should consider using higher temporal resolution data (e.g., monthly series) and incorporating additional environmental and social variables to improve model accuracy. The integration of ensemble forecasting methods and prediction intervals is also recommended to enhance robustness and uncertainty estimation. Furthermore, continuous model updating and data monitoring are essential to ensure the sustainability of this approach as a decision-support system.

In conclusion, this study found that dengue transmission in East Java is significantly driven by both specific meteorological variables and spatially varying social vulnerabilities. While global models highlighted Rainfall and Humidity as the primary natural determinants, the application of the Geographically Weighted Regression (GWR) framework provided a crucial advancement by uncovering the spatial non-stationarity of social factors, such as population density. The novelty of this analytical framework lies in its ability to map localized risk indices, revealing that high-risk social clusters are heavily concentrated in the eastern 'Tapal Kuda' region and northern coastal metropolitan corridors. Practically, these findings offer a vital contribution to public health management. By moving beyond a 'one-size-fits-all' approach, the localized insights generated from this spatial framework enable local health authorities and policymakers to design targeted, location-specific mitigation strategies, ensuring that limited resources are allocated more effectively to the most vulnerable districts.

AUTHOR CONTRIBUTION

Budi Fajar Supriyanto served as the principal investigator, developed the original concept, conducted the statistical analyses, and generated the spatial result maps. Ikha Nurjihan and Andi Mulyanti Suhartini were responsible for data acquisition and curation. Nesa Ayu Murthisari Putri provided expert insights and validation in epidemiology. Elsa Tursina drafted and wrote the manuscript. All authors have read and agreed to the published version of the manuscript.

FUNDING AND SPONSORSHIP

None.

ACKNOWLEDGEMENT

The author wishes to extend heartfelt thanks to Statistics Indonesia (*Badan Pusat Statistik*/ BPS) Ngawi Regency and Statistics Indonesia of East Java Province, the Ministry of Health of the Republic of Indonesia, the Geospatial Information Agency/ *Badan Informasi Geospasial* (BIG), and Environmental Systems Research Institute (ESRI) for generously providing the datasets utilized in this research. These data have been instrumental in the successful completion of this study.

CONFLICT OF INTEREST

The authors declare that there's no conflict of interest in this study.

REFERENCES

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

Chen Z, Zhang S, Geng W, Ding Y, Jiang X. (2022). Use of Geographically Weighted Regression (GWR) to Reveal Spatially Varying Relationships between Cd Accumulation and Soil Properties at Field Scale. Land. 11(5): 635. https://doi.org/10.3390/-land11050635.

Cunha MS, Coletti, TM Guerra JM, Ponce CC, Fernandes NCCA, Résio RA, Claro IM, et al., (2022). A fatal case of dengue hemorrhagic fever associated with dengue virus 4 (DENV-4) in Brazil: genomic and histopathological findings. Braz J Microbiol. 53(3): 1305–1312. https://doi.org/10.1007/-s42770-022-00784-4.

Damtew YT, Tong M, Varghesea BM, Anikeevaa O, Hansena A, Dearaet K, al. (2023). Effects of high temperatures and heatwaves on dengue fever: a systematic review and meta-analysis. EBioMedicine. 91: 104582. https://doi.org/10.1016/j.ebiom.2023.104582.

de Souza WM, Weaver SC. (2024). Effects of climate change and human activities on vector-borne diseases. Nature Rev Microbiol. 22(8): 476–491. https://doi.org/10.1038/s41579-024-01026-0.

Faridah L, Suroso DSA, Fitriyanto MS, Andari CD, Fauzi I, Kurniawan Y, Watanabe K. (2022). Optimal validated multi-factorial climate change risk assessment for adaptation planning and evaluation of infectious disease: A case study of dengue hemorrhagic fever in Indonesia. Trop Med Infect Dis. 7(8): 172. https://-doi.org/10.3390/tropicalmed7080172

Fotheringham AS, Yu H, Wolf LJ, Oshan TM, Li Z. (2022). On the notion of 'bandwidth' in geographically weighted regression models of spatially varying processes. Int J Geogr Inf Sci. 36(8): 1485–1502. https://-doi.org/10.1080/13658816.2022.2034829.

Gupta G, Khan S, Guleria V, Almjally A, Alabduallah BI, Siddiqui T, Albahlal BM, et al. (2023). DDPM: A Dengue Disease Prediction and Diagnosis Model Using Sentiment Analysis and Machine Learning Algorithms. Diagnostics. 13(6): 1093. https://doi.org/-10.3390/diagnostics13061093.

Kontopoulou VI, Panagopoulos AD, Kakkos I, Matsopoulos GK. (2023). A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. Future Internet. 15(8): 255. https://doi.org/-10.3390/fi15080255.

Li J, Guo SX, Ma RL, He J, Zhang XH, Rui DS, Ding YS, et al., (2024). Comparison of the effects of imputation methods for missing data in predictive modelling of cohort study datasets. BMC Med Res Methodol. 24(1): 41. https://doi.org/10.1186/s12874-024-02173-x.

Liu Y, Feng G, Chin KS, Sun S, Wang S (2023). Daily tourism demand forecasting: the impact of complex seasonal patterns and holiday effects. Curr Issues Tour. 26(10): 1573–1592. https://doi.org/10.1080/13683500.2022.2060067.

Na L, Shi Y, Guo L. (2023). Quantifying the spatial nonstationary response of influencing factors on ecosystem health based on the geographical weighted regression (GWR) model: an example in Inner Mongolia, China, from 1995 to 2020. Environ Sci Pollut Res. 30(29): 73469–73484. https://-doi.org/10.1007/s11356-023-26915-4.

Oh J, Seong B. (2024). Forecasting with a combined model of ETS and ARIMA.

Commun Stat Appl Methods. 31(1): 143–154. https://doi.org/10.29220/-CSAM.2024.31.1.143.

Parveen S, Riaz Z, Saeed S, Ishaque U, Sultana M, Faiz Z, Shafqat Z, al., (2023). Dengue hemorrhagic fever: a growing global menace. J Water Health. 21(11): 1632–1650. https://-doi.org/10.2166/wh.2023.114.

Perone G. (2022). Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. Eur J Health Econ. 23(6): 917–940. https://doi.org/10.1007/s10198-021-01347-4.

Riaz M, Harun SNB, Mallhi TH, Khan YH, Butt MH, Husain A, Khan MM, et al., (2024). Evaluation of clinical and laboratory characteristics of dengue viral infection and risk factors of dengue hemorrhagic fever: a multi-center retrospective analysis. BMC Infect Dis. 24(1): 500. https://doi.-org/10.1186/s12879-024-09384-z

Sudarmaja IM, Swastika IK, Diarthini LPE, Prasetya IPD, Wirawan IMA (2022). Dengue virus transovarial transmiss-ion detection in Aedes aegypti from dengue hemorrhagic fever patients' residences in Denpasar, Bali. Veterinary World. 1149–1153. https://doi.-org/10.14202/vetworld.2022.1149-1153.

Wang H, Huang Z, Guo H, Yin G, Bao Y, Zhou X, Gao Y, et al. (2026). GWR-Boost: A Geographically Weighted Gradient Boosting Framework for Enhanced Explainable Quantification of Spatially Varying Relationships. Ann Am Assoc Geogr. 1–19. https://-doi.org/10.1080/24694452.2026.2648327.

Wang Q, Gayed JM. (2026). Effectiveness of large language models in automated evaluation of argumentative essays: finetuning vs. zero-shot prompting. Comput Assist Lang Learn. 39(1–2): 209–237. https://-doi.org/10.1080/09588221.2024.2371395.

Yang W, Deng M, Tang J, Luo L. (2023). Geographically weighted regression with the integration of machine learning for spatial prediction. J Geogr Syst. 25(2): 213–236. https://doi.org-/10.1007/s10109-022-00387-5.

Zhao D, Zhang H. (2022). The research on TBATS and ELM models for prediction of human brucellosis cases in mainland China: a time series study. BMC Infect Dis. 22(1): 934. https://-doi.org/10.1186/s12879-022-07919-w.