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A Spatial Analysis on Heterogenous Determinant of Dengue Fever Cases in Indonesia

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Abstract

The high prevalence of dengue fever continues to be a significant issue in Indonesia. This study examines dengue fever cases in Indonesia through a spatio-temporal lens, utilizing panel data from 2017 to 2022 across 34 provinces. The analysis integrates multiple explanatory factors to assess their influence on dengue incidence. The findings indicate that higher population density, improved access to sanitation, and increased GDP per capita are all associated with elevated dengue fever cases. The study further explores the varying effects of the Gini ratio and government health expenditure on dengue incidence, revealing significant regional disparities. Notably, meteorological factors, particularly humidity, play a substantial role in dengue transmission nationwide. Population density exacerbates dengue incidence, particularly in the densely populated eastern regions. Improved sanitation access is positively linked to dengue cases, suggesting that inadequate maintenance of sanitation infrastructure may create mosquito breeding sites. Additionally, higher GDP per capita is associated with increased dengue infections, implying that greater economic development can facilitate higher population mobility and, thereby increasing risk of transmission. The Gini ratio and government health spending exhibit varying impacts on dengue incidence. In general, the Gini ratio correlates positively correlated with dengue risks, but shows an inverse relationship in Papua and West Papua, indicating that dengue transmission is not exclusively confined to low socioeconomic regions. Public health expenditure is effective in reducing dengue cases in certain regions but is less impactful in others, underscoring the importance of efficient resource allocation and governance. Finally, meteorological factors, notably higher temperatures, correlate with higher dengue incidence, while heavy rainfall can disrupt mosquito breeding, leading to a reduction in cases.

Keywords Dengue fever · Spatial–temporal analysis · Inequality · Socioeconomic factors · Meteorological impact

Introduction

Dengue fever poses a persistent threat to public health, affecting tropical, subtropical, and even temperate regions (WHO 2023). Once a localized concern, it has burgeoned into a global pandemic, with *Aedes* mosquitoes serving as the primary vectors, spreading the virus worldwide (Pathak & Mohan 2019). These mosquitoes thrive near human habitation, exploiting stagnant water sources for breeding and enabling rapid virus transmission, particularly in densely populated areas. Research highlights a correlation between dengue fever incidence and seasonal variations, with outbreaks often peaking during both dry and wet seasons (Fauzi et al. 2019). The looming specter of outbreaks, compounded by a lack of proactive measures, underscores the need for preemptive action, especially pronounced in the wet season when mosquito breeding rates escalate. This urgency is especially pronounced in Indonesia, a nation grappling

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with significant population density and challenges in water sanitation infrastructure amidst diverse climatic conditions.

Indonesia reports over 100,000 cases of dengue fever annually, establishing it as a hotspot for the disease and a prime environment for *Aedes* mosquito proliferation (Harapan et al. 2019). Effectively combating outbreaks and mitigating the disease's impact require a nuance understanding of its spatial and temporal dynamics. Given the regional heterogeneity o dengue transmission, interventions must be tailored to local characteristics, emphasizing a region-specific approach over one-size-fits-all strategy.

Dengue fever incidence is shaped by a complex interplay of environmental, socioeconomic, and institutional factors. Temperature and rainfall significantly influence mosquito development and population dynamics, with elevated temperatures accelerating virus transmission and rainfall creating abundant breeding habitats (Acharya et al. 2016; Astuti et al. 2019). Socioeconomic factors, including low housing standards and limited access healthcare, further exacerbate the burden on vulnerable populations (Casas & Delmelle 2019; Chu et al. 2016; Delmelle et al. 2016; Qi et al. 2015).

Indonesia's landscape presents several unique factors that influence the spread of dengue fever, including its tropical climate, diverse geography, urbanization patterns, and socioeconomic conditions (Kraemer et al. 2015). The consistently warm temperatures and high humidity in the country provide an ideal environment for *Aedes* mosquitoes (Lai 2018), the primary vectors of dengue, supporting continuous mosquito breeding and transmission throughout the year. The geographic diversity of Indonesia, spanning from densely populated urban areas to remote rural regions, presents distinct challenges for dengue control. In urban areas, high population density promotes the rapid spread of the disease due to close human contact and numerous breeding sites. In contrast, rural areas often face limited access to healthcare and mosquito control measures, exacerbating the difficulty of managing dengue outbreaks. For instance, Fauzi et al. (2022) found a notable increase in confirmed dengue cases between January and March. During this period, more than two-thirds (70.4%) of the regions in West Java experienced a peak in dengue infection, with the highest rates occurring from the first week of January to the second week of March.

Additionally, improper water storage practices, particularly in regions where containers and tanks are left uncovered, provide ideal breeding grounds for mosquitoes (Akanda et al. 2020). Poor waste management in some areas, further exacerbates the issue, as accumulated trash and stagnant water, create habitats for mosquitoes when discarded items collect rainwater (Akanda et al. 2020). The monsoon season's heavy rains further increase mosquito breeding sites by creating more standing water, which correlates with spikes in dengue cases. Moreover, water storage practices are closely linked to household behavior that can help mitigate the larval development. As highlighted by Padmanabha et al. (2010), Tran et al. (2010), and Trewin et al. (2021), household sanitation practices significantly influence community-level dengue risk. This hypothesis is supported by a study in China, which found that improved sanitation could reduce the incidence of dengue fever (Wu et al. 2022). These literature reviews collectively underscore the crucial role of sanitation in dengue control.

In the Indonesian context, the annual rise in dengue cases is closely linked to inadequate environmental sanitation. According to Setyadi et al. (2021), poor sanitation practices—such as improper drainage in bathtubs, leaving water containers uncovered both indoors and outdoors, inadequate waste management that lead to garbage accumulation, and failure to properly dispose of used cans and other items—significantly contribute to this issue by creating ideal breeding grounds for *Aedes* mosquitoes.

The Indonesian government has increased its budget and investment in basic sanitation, leading to improvements in access. By 2021, 80.29% of the population had access to improved sanitation (Sanitation and Water for All 2022). While this progress is essential for maintaining water and sanitation services, access remains uneven, particularly among the poorest 40%, remaining underserved. Odagiri et al. (2020) noted that the proportion of households gaining access to private toilets in high-intensity districts ranged from only 8 to 27%, highlighting significant disparities that require urgent attention. As Indonesia bears one of the world's highest dengue burdens, with *Aedes aegypti* as the primary vector and *Aedes albopictus* as the secondary vector (Nadjib et al. 2019), an integrated approach to improving sanitation, waste management, and public awareness is crucial to mitigating the disease's spread.

Socioeconomic factors, such as income levels, education, and access to healthcare, play a crucial role in determining a community's ability to manage and prevent dengue. Lower-income areas often lack infrastructure for mosquito control and public health education (Lai et al. 2019; Seposo et al. 2023; Watts et al. 2020). Additionally, rapid urbanization has often led to the proliferation of slum areas, where the poorer segments of society are more vulnerable to dengue (Qu et al. 2018). Another important determinant is the Gini coefficient which measures inequality. Inequality both within and between regions can indirectly affect health outcomes and may increase the fatality risk of dengue fever (Da Conceição Araújo et al. 2020; Pone et al. 2018). Bambra (2022) explains how the Gini coefficient influences disease outcomes through mechanism such as by unequal exposure, transmission, susceptibility, and access to treatment. Low-income households often cannot afford preventive tools, while limited education and restricted healthcare access exacerbate the problem, creating barriers to effective dengue control.

In response, the Indonesian government launched the "3 M Plus" campaign, emphasizing three key actions for dengue prevention: draining, covering, and recycling to eliminate mosquito breeding grounds. Despite these efforts, dengue incidence remains high (Karyanti et al. 2014). To further address this, the Indonesian Ministry of Health introduced the *Healthy Indonesia Program* in 2016, with the "Satu Rumah Satu Jumantik" initiative, designing designating family members to monitor mosquito larvae (Rakhmani and Zuhriyah, 2024; Rakhmani et al. 2021). However, the program's success is often tied to better-educated, higher-income households, which are more likely to participate actively (Shuaib et al. 2010).

Understanding the spatiotemporal dynamics of dengue fever becomes crucial in predicting and effectively managing outbreaks (Shabbir et al. 2020). Incorporating spatiotemporal analysis involves studying the distribution of the disease over time and space, revealing patterns and trends that may not be evident when examining data solely from a temporal or spatial perspective, especially in Indonesian context. This comprehensive approach helps identify high-risk regions and better understand how the disease spreads within and between regions. Additionally, It allows for the integrations of various variables, such as environmental factors, socioeconomic conditions, and demographic characteristics, which are crucial in elucidating the regional characteristics correlated with dengue fever cases (Fauzi et al. 2022; Yue et al. 2018).

By analyzing these variables, public health authorities can gain insights into the factors driving dengue transmission in different regions. This knowledge is vital for tailoring interventions to the specific needs of each region, ensuring that resources for prevention and control are allocated effectively. Such targeted approaches can be implemented by the regional government to maximize the effectiveness of public health efforts. Thus, a spatiotemporal analysis not only enhances our understanding of the current epidemiological landscape but also supports the planning and implementation of more efficient and effective public health interventions. This study aims to unravel the complex dynamics of dengue fever incidence in Indonesia, examining its determinants at the provincial level and assessing its spread across neighboring regions. Using comprehensive dataset that includes dengue fever cases, climate variables, and socioeconomic indicators, the research aims to elucidate the complex interplay of factors influencing the disease's propagation over space and time. In essence, this research aims to provide a comprehensive spatial and temporal perspective on dengue fever in Indonesia, enriching the knowledge base to inform evidence-based policymaking tailored to each province's unique context. By addressing the central question of dengue fever's spatial and temporal dynamics, this study endeavors to catalyze targeted interventions and optimize resource allocation, thereby advancing the quest for effective disease control and prevention strategies.

Data and Methodology

Study Area

Indonesia is an archipelago country with more than 17,000 islands. Geographically, it is located in the middle of two continents, Asia and Australia, with latitude 9°U-11°S and 90°E-141°E. Due to its proximity to the equator, Indonesia experiences a tropical climate across the country. The warm humid temperatures create a suitable habitat for mosquitos, increasing the transmission risk of various vector-borne diseases, including dengue fever. Moreover, the annual rainy season in tropical regions could escalate the number of mosquito breeding sites, which poses a threat of dengue fever outbreaks. As an archipelago, Indonesia exhibits diverse pattern of dengue fever incidences. Figure 1 illustrates the spatial distribution of dengue cases in Indonesia during the 2017 to 2021. During these periods, an average of 444,597 dengue cases have been recorded, with significant regional variations, especially when considering the number of cases per 100,000 people. This uneven distribution can attributed to the diverse characteristics of Indonesia's region.

Data

The present study examines dengue fever cases in Indonesia through spatial–temporal lens, using panel data that span from 2017 to 2022 across 34 provinces. This current study incorporates several explanatory factors to assess their impact on dengue fever incidences. The detailed information for each variable in this study is shown in Table 1.

Dengue infection is more prevalent on Java Island which is the most populated area in Indonesia. Table 2 underscores this issue by demonstrating not only the uneven distribution of diseases but also the diverse socioeconomic and meteorological characteristics across provinces. These disparities are reflected in the relatively high standard deviation value, for example, the government spending per capita that has a standard deviation of 4.022, with a value ranging from a minimum of 0.038 to a maximum of 25.370.

This study applied several strategies to analyze dengue fever case within spatiotemporal approach. First, we adopted a Lorenz curve and Gini index to explore the spatial heterogeneity of dengue fever spread across regions in Indonesia. The Lorenz curve informs a cumulative distribution of disease and population through a graphical visualization (Chowell et al. 2008). Meanwhile, Gini index is derived from Lorenz curve and can be calculated through the following mathematical expressions.

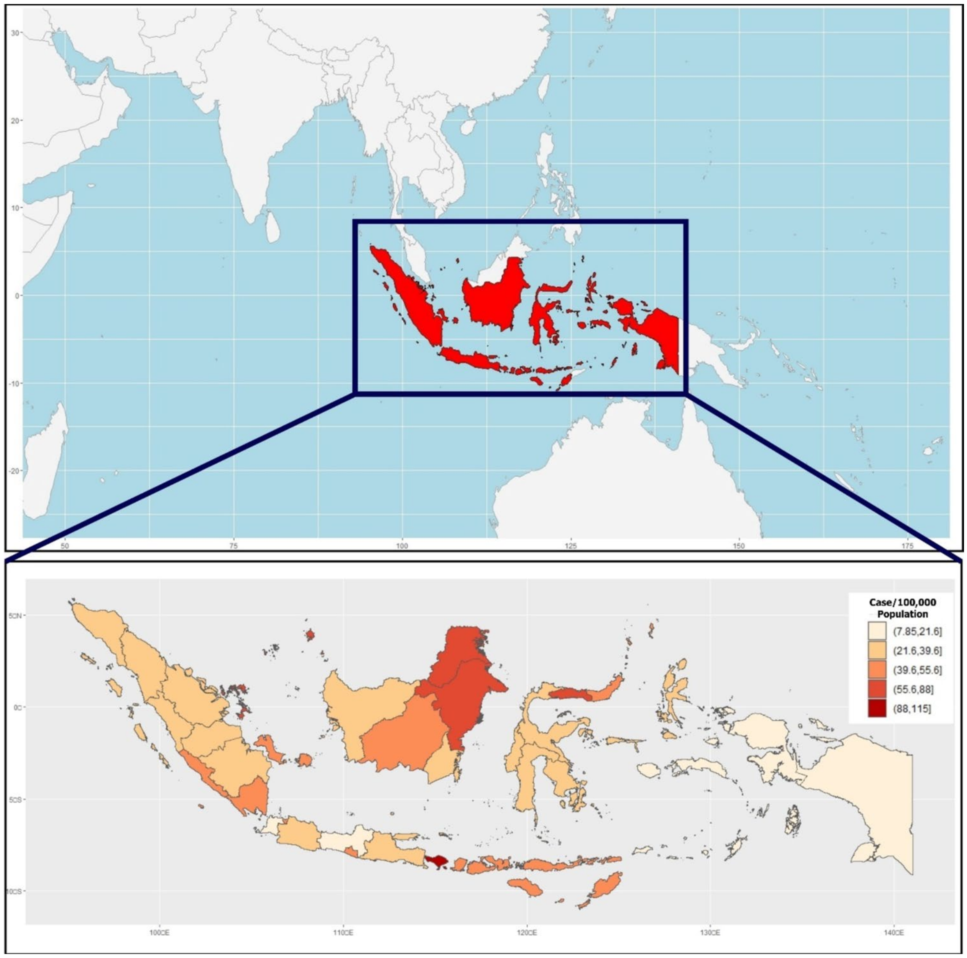

Fig. 1 The study area location and dengue fever cases distribution. The legend depicts the province's dengue fever incidence (the darker color means the higher cases occurred). Source: Indonesia Ministry of Health (processed)

Table 1 List of variables

Variables	Measurement	Data sources
Dengue fever cases	Total dengue fever incident	Indonesia Ministry of Health
Population density	Percentage of household with area occupancy, less than 7.2 m^2 per capita	Statistics Indonesia (BPS)
Improved sanitation access	Total number of households who has better access of sanitation	Statistics Indonesia (BPS)
GDP per capita	Total GDP divided by total population	Statistics Indonesia (BPS)
Gini ratio	Coefficient of inequal income distribution in certain region, 0 = perfectly equal distributed, 1 = perfectly inequal distributed	Statistics Indonesia (BPS)
Government spending on health per capita	Total government spending on health, divided by total population	Statistics Indonesia (BPS)
Temperature	Average temperature, yearly (°C)	Statistics Indonesia (BPS)
Precipitation	Total precipitation, yearly (mm)	Statistics Indonesia (BPS)
Humidity	Average humidity, yearly (%)	Statistics Indonesia (BPS)

$$G = 2\left(\sum_{i=1}^{N} \frac{1}{2}(P_n - P_{n-1})(C_n + C_{n-1})\right) - 1 \tag{1}$$

where i refer to spatial unit, N is total unit of observation, C represent the cumulative proportion of dengue fever cases within provinces, and P denotes cumulative proportion of population. The Gini index value ranges from 0 to 1, if $G = 0$ than it indicates that dengue fever cases are perfectly distributed proportionally to population size, while when $G = 1$ it means the dengue fever is concentrated in single observation unit (Fadilah et al. 2022).

Table 2 Descriptive statistics

Variables	N	Mean	Std. dev	Min	Max
Dependent variable					
Log natural of dengue fever cases	170	7.191	1.236	3.611	10.084
Socioeconomic condition					
Population density (%)	170	9.801	5.878	1.350	35.390
Improved sanitation access (%)	170	74.376	13.010	32.560	97.120
Log natural GDP per capita	170	10.482	0.543	9.381	12.073
Gini ratio	170	0.351	0.038	0.247	0.440
Government spending on health per capita (Million Rupiah)	170	2.056	4.022	0.038	25.370
Meteorological factors					
Temperature (°C)	170	27.817	0.980	24.900	30.000
Log natural of precipitation	170	7.766	0.395	6.195	8.617
Humidity (%)	170	80.204	4.523	69.000	91.000

Source: data processing output

Then, the current study performs the Geographical Weighted Regression (GWR) to explore the relationship between dengue fever cases and its explanatory factors. This method offers the advantage of examining how these relationships vary at the spatial level, as they may differ across units (Lotfata 2022; Mahmood et al. 2019). The GWR model can be defined through this formula.

$$DF_i = \beta_0(i) + \sum_{k=1}^{K} \beta_k X_k(i) + \varepsilon_i \tag{2}$$

DF_i denotes the number of dengue fever case in i, 0 is local intercept, k is a coefficient for each k-th independent variable, and i as the error terms. The GWR results can be interpreted into the map to shows how the variables can determine the dengue fever incidence in every spatial unit.

The Geographically Weighted Panel Regression Method (GWR)

This research employs the Geographically Weighted Panel Regression (GWR) method, an advanced technology for geographically cross-sectional analysis (McMillen, 2004; Yu et al. 2021). The method was originally developed by Yu (2010, 2014) to analyze regional development using spatial aspects in economic modeling. GWR offers deeper insights into spatial relationships by explaining selected variables more thoroughly (Yu et al. 2021). Seya et al. (2011) explain that GWR's use of Weighted Least Squares (WLS) and the Gauss-Markov theorem sets it apart from other spatial econometric models. While GWR focuses on spatial heterogeneity, global spatial econometric models emphasize spatial dependence and spillover effects (Geniaux and Martinetti 2018; Zhao et al. 2021). Similar studies in countries like Brazil (Castro et al. 2021; Do Carmo et al. 2020; Mondini and Chiaravalloti-Neto 2008), China (Qu et al. 2018; Yue et al. 2018), Vietnam (Ashmore et al. 2020), and Nepal (Acharya et al. 2016) have successfully applied the GWR method. Thus, one of the key strengths of choosing the Geographically Weighted Regression (GWR) for this study is its ability to capture spatially varying relationships between variables. The general form of the GWR model can be expressed as follows:

$$y_{1;T} = X_{1;T}\beta_{1;T} + N_{1;T}\gamma_{1N} + TM_{1;T}\gamma_{TM} + \varepsilon_{1;T}, \varepsilon_{1;T} \sim N(0_{1;T}, \delta^2 I_{1;T}) \tag{3}$$

where $y_{1;T}$ is explaining the dependent variables over T time periods, $X_{1;T}$ is the independent variables with $\beta_{1;T}$ as the coeffiecient, $N_{1;T}\gamma_{1N}$ is showing the individual observation for specific effect, and $TM_{1;T}\gamma_{TM}$ is showing the temporal specific effects (Greene 2003).

Result and Discussion

Spatial Heterogeneity of Dengue Cases

The heterogeneity of dengue infection in Indonesia is represented by the Gini index, which is illustrated in the Lorenz curve (see Fig. 2). The Gini index for dengue incidence remains relatively stable at values above 0.300, indicating the existence of regions with disproportionately high cases number. Although the Gini index dropped to 0.238 in 2019, it returned to pre-pandemic levels during 2020 and 2021. During the COVID-19 pandemic, the Indonesian government implemented physical distancing measures, which helped limit the spread of the virus between regions. This restriction on movement may have also influenced dengue fever cases, as infected individuals were less able to travel between provinces. As a result, dengue infections became more localized during this period. The rise in the Gini index

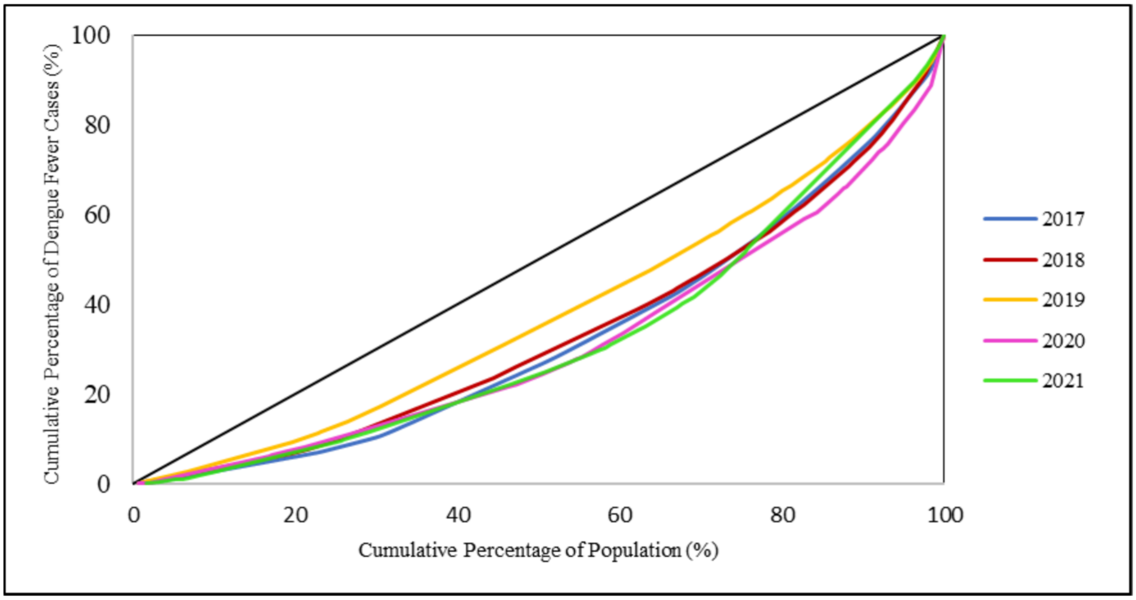

Fig. 2 Lorenz curve of dengue fever cases in Indonesia 2017–2021. Source: data processing output

score suggest that regional differences in dengue infections are influenced by varying provincial characteristics. However, the Gini index alone does not identify the specific factors driving this regional disparities. Therefore, further analysis is necessary to gain a better understanding of this issue.

Figure 3 displays a further analysis of how dengue fever cases spread across provinces in Indonesia during the study period. Figure 3. demonstrates the concentration of dengue fever incidence in specific region and at particular time point. Notably, in 2020 and 2021, dengue fever cases were concentrated in several regions, especially Bali. This pattern raises the important concern as the increases in the Gini index score and the concentration of dengue cases in certain areas suggest that dengue infections may be influenced by the varying characteristics of different provinces. However, the Gini index does not pinpoint the specific factors driving this regional disparities. As result, further analysis is necessary to gain a better understanding of this issue.

Spatial Regression

The present study compares the goodness fit between two models, namely, GWR (Geographically Weighted Regression) and FE-OLS (Fixed Effects Ordinary Least Squares). As in Table 3, GWR provides a better fit than the FE-OLS model. Specifically, GWR exhibits smaller value of AIC (Akaike Information Criterion) and RSS (Residual Sum of Squares), while also yielding higher value of R^2 and adjusted R^2 compared to the FE-OLS model. These results indicate that GWR provides a superior fit for examining the effect of explanatory variables on dengue fever cases in this research.

The GWR model captures the location-specific heterogeneous effect of variables on dengue fever at local level. Three types of spatial weights can be applied in GWR model, namely, Bisquare, Gaussian, and Tricube. Given that Bisquare offers the highest goodness of fit, the present study opts to use the Bisquare spatial weight matrix over the others (see Table 4). The estimated GWR coefficients are summarized in Table 5. The result show that in a global regression, only four variables significantly influence dengue fever incidence across Indonesia provinces. Population density, improved sanitation access, and GDP per capita contribute to higher dengue fever cases, while precipitation is found significantly decrease dengue fever incidence in Indonesia.

This study also seeks to provide more accurate results by presenting the GWR estimation for each province. Figure 4 illustrates that the local R^2 values vary across regions in Indonesia. Notably, Aceh exhibits the highest goodness of fit (local $R^2 = 0.883$), while Papua has the lowest local R^2 among the provinces. However, even Papua's local R^2 value (0.246) exceeds the FE-OLS model, further reinforcing that the GWR model is the more suitable choice for this research.

Figure 5 illustrates the coefficient of independent variables that significantly influence the infection of dengue fever across different regions of Indonesian. The impact of each variable on dengue fever varies considerably, highlighting the need for region-specific interventions. (1) Population density, the Gini index, and government spending have a more pronounced effect on dengue cases in the eastern part of Indonesia. In contrast, temperature and humidity significantly influence dengue infections in the western provinces. Additionally, variables such as sanitation access, GDP per

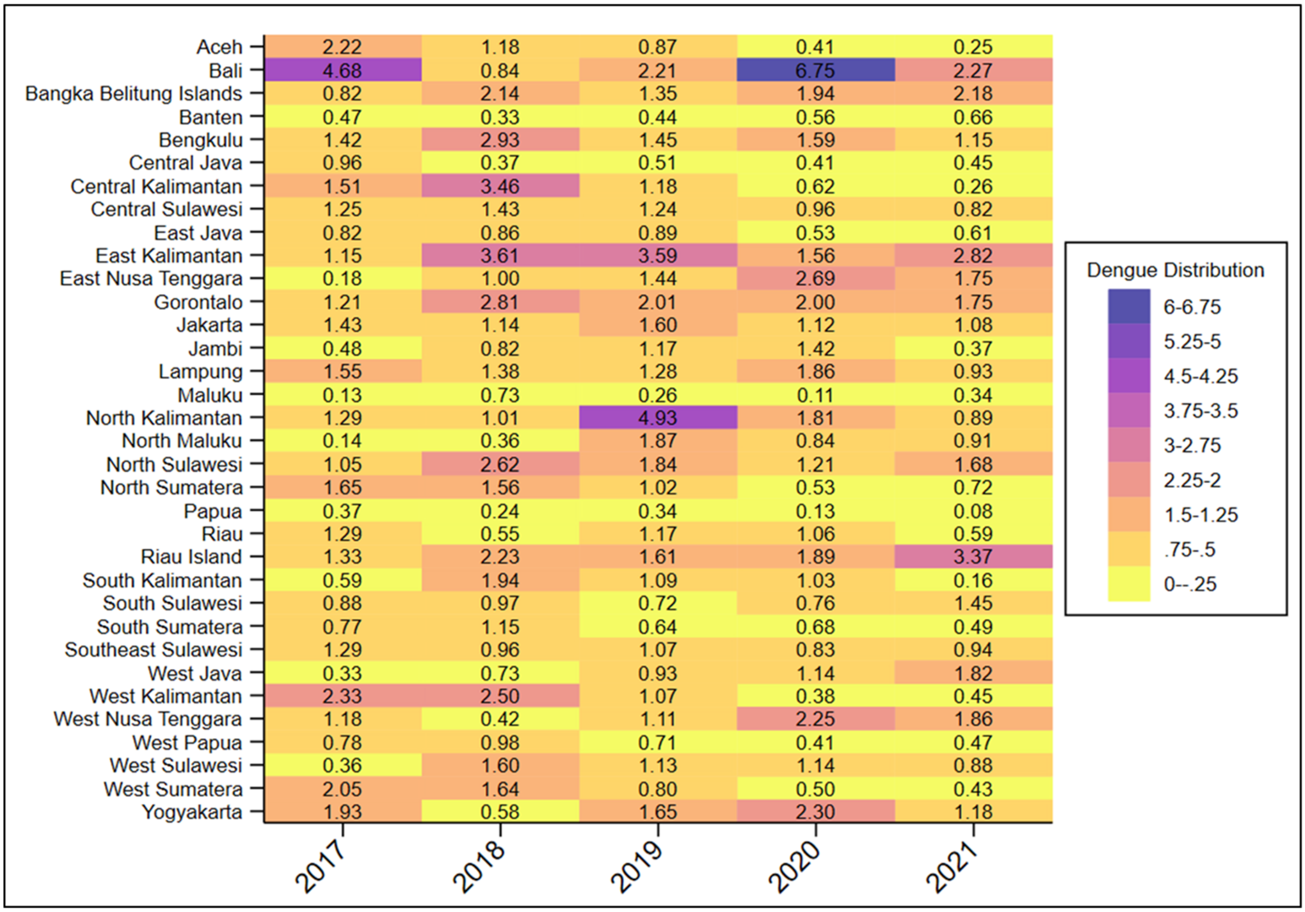

Fig. 3 Dengue fever incidence dynamics across provinces. The dengue (fever cases) distribution is measured by dividing the proportion of provincial dengue fever incidences in the national to the proportion of provincial population in the national. Source: data processing output

Table 3 Fittest test comparison between GWR and FE-OLS

Parameters	GWR	FE-OLS
AIC	214.222	307.578
R^2	0.628	0.226
R^2-adj	0.419	−0.021
RSS	26.272	54.670

Source: data processing output

Table 4 The estimated spatial weight matrix

Weight decay type	Dependent variable: dengue fever incidence		
	Bisquare	Gaussian	Tricube
RSS	26.272	35.276	27.211
R^2	0.628	0.501	0.615
R^2-adj	0.420	0.319	0.422
CV	51.575	53.164	52.193

Source: data processing output

capita, and precipitation have a significant effect on dengue cases in nearly all provinces. (2) The GWR estimation further reveals that the impact of these variables varies across provinces. For instance, the Gini index generally correlates with an increase in dengue cases (positive correlation) in most regions, except for West Papua and Papua provinces. Similarly, government spending appears to increase dengue fever in Central Java and Yogyakarta. Given these diverse outcomes from the GWR analysis, further investigation and targeted discussions are necessary to fully address dengue fever cases in Indonesia.

Discussion

The Evidence of Dengue Incidence Spread

Our analysis of the Dengue Fever Gini ratio (Fig. 2) and its spread (Fig. 3) reveals that while dengue fever incidence is widespread across Indonesia, certain regions experience a disproportionately high number of cases. Our findings align

Table 5 GWR panel result

Variables	Global	GWR panel				
		Min	1st Qu	Mean	3rd Qu	Max
Population density	0.139***	−0.012	0.01	0.032	0.059	0.088
Improved sanitation access	0.026***	0.017	0.111	0.164	0.207	0.425
Log natural GDP per capita	1.657*	−2.84	−0.677	2.32	5.545	11.369
Gini ratio	2.15	−23.486	−12.328	3.03	13.787	28.219
Government spending on health per capita	−0.012	−0.109	−0.028	0.057	0.096	0.472
Temperature	0.098	−0.533	−0.151	0.024	0.213	0.546
Log natural of precipitation	−0.83***	−1.463	−1.144	−0.811	−0.638	0.121
Humidity	0.037	−0.078	−0.013	0.019	0.062	0.101

Source: data processing output

***$p<0.01$, **$p<0.05$, and *$p<0.1$

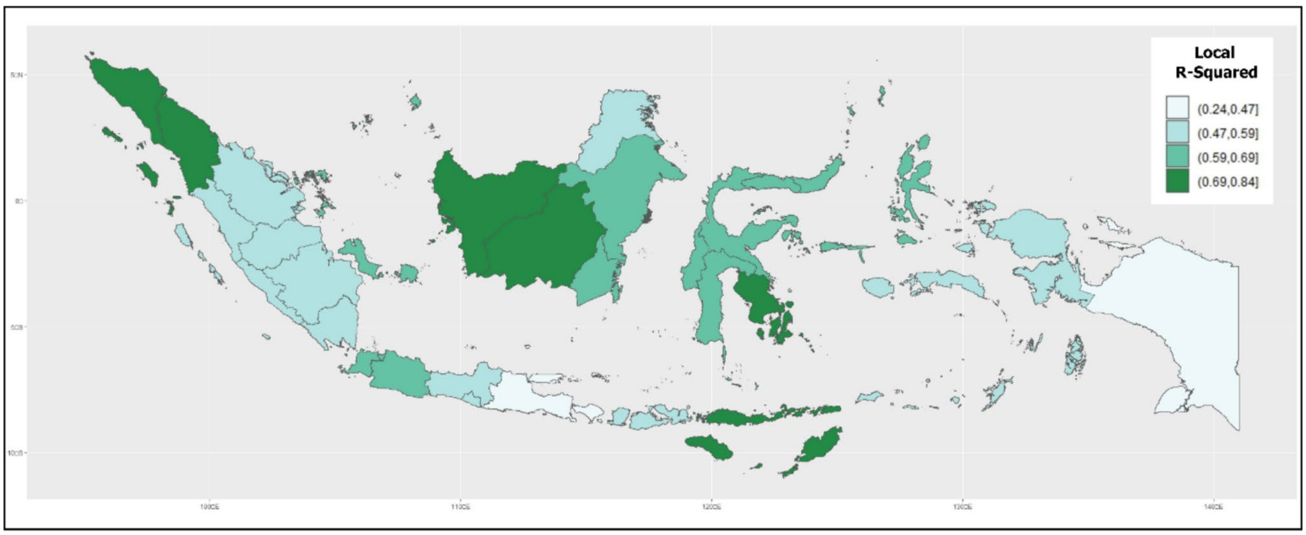

Fig. 4 Local R^2 distribution. The legend shows the local R^2 values for each province (darker colors indicate higher R^2 scores, reflecting the extent to which the independent variables explain dengue case incidence in the region). Source: data processing output

with the previous studies conducted in different archipelago countries, including the Dominican Republic (Petrone et al. 2021), the Philippines (Seposo et al. 2023), and French Polynesia (Teissier et al. 2020), which have found that while dengue fever is widely dispersed, specific hotspot exists within these nations. This suggests that dengue fever is spatially heterogeneous and may be closely associated with the unique local characteristics of each regions.

Increase Population Density, Improved Sanitation Access, and Higher GDP per Capita Contribute to Rising Dengue Fever Cases

The findings confirm that population density is associated with a 13% increase in dengue cases in Indonesia. This result aligns with studies by Do Carmo et al. (2020) and Wu et al. (2009), which similarly observed that a highly populated area are at greater risk of dengue fever infection. Notably, the coefficient for population density in the present findings is slightly higher than those reported in Brazil (10%) (Do Carmo et al. 2020) and in Taiwan (11%) (P.-C. Wu et al. 2009). Studies in Indonesia have produced similar findings, with population density coefficients around 17% (Dhewantara et al. 2019; Tam et al. 2018). Interestingly, our study also reveals that the population density significantly influences dengue fever cases in the eastern part of Indonesia. While these regions generally have a lower population density compared to the western part (Fig. 4), many households in the eastern provinces reside in overcrowded conditions with less than 7.2 m^2 of living space per capita. This suggests that even areas with relatively low population density can experience increased dengue transmission due to poor

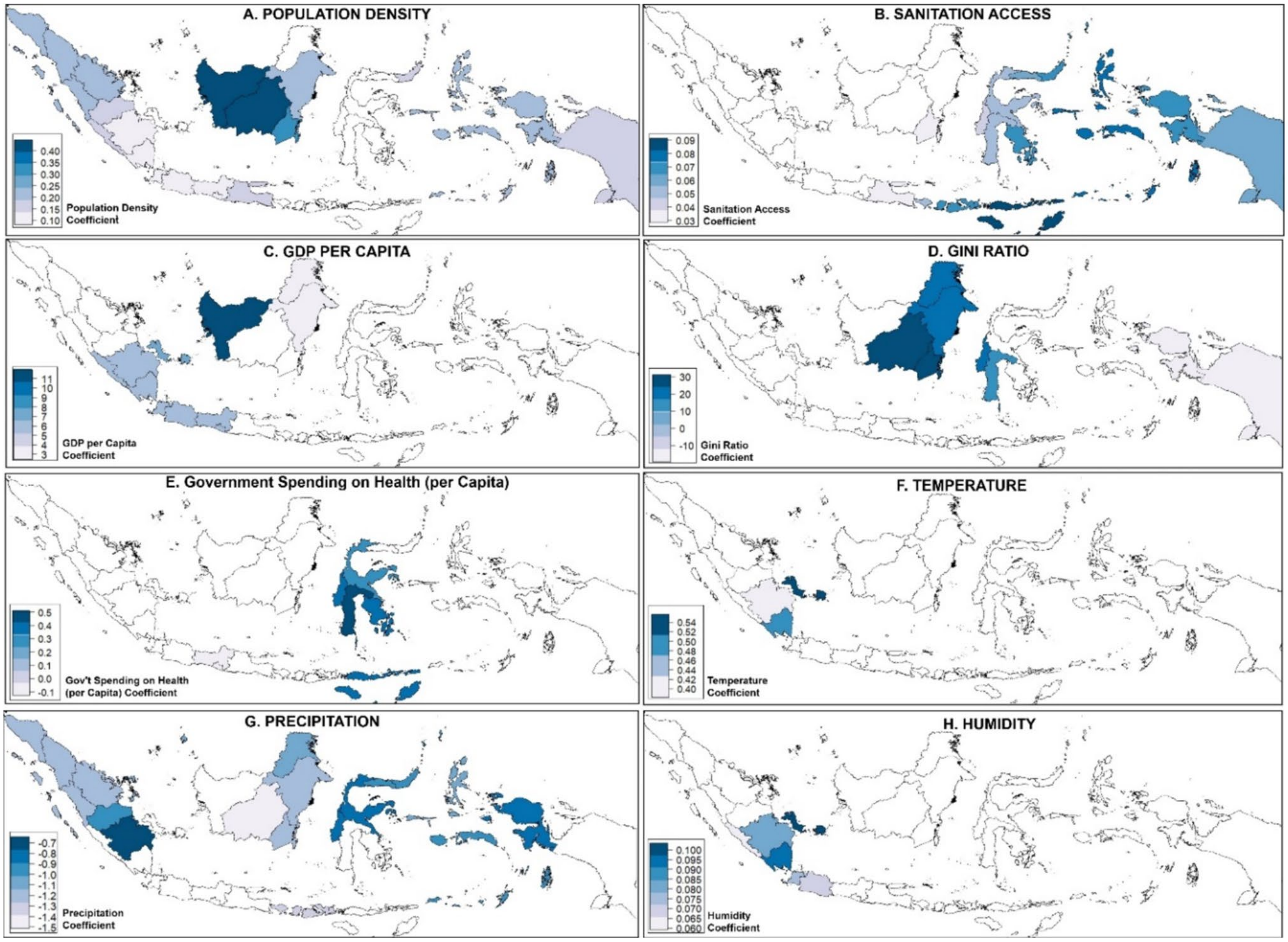

Fig. 5 Explanatory variable coefficient in Geographically Weighted Panel Regression (GWR) results for each province in Indonesia. Source: data processing output

housing conditions. According to Mamenun et al. (2024), the relationship between population density and dengue cases is influenced by extreme climate factors, which contributes to the eastern part of Indonesia the fourth hotspot for dengue. Previous studies have also shown that high household density increases the risk of dengue infection as it creates favorable conditions for mosquito breeding and transmission (Kenneson et al. 2017).

An intriguing finding from our study is the positive association between improved sanitation access and dengue fever cases with an increase around 2.6%. This outcome challenges the mainstream literatures, which typically emphasizes the positive impact of improved sanitation access in reducing dengue cases (Almeida et al. 2020; Sangar & Thakur 2022). However, a similar trend was observed by Oliveira et al. (2023), who found that cities with better sanitation infrastructure were still highly correlated with higher dengue fever incidence. This suggests that while sanitation is a crucial factor in controlling mosquito-borne diseases, its effectiveness may be influenced by other local conditions, such as maintenance, public behavior, and climate factors. According to Telle et al. (2021), higher dengue cases are associated with better sanitation levels, potentially due to the movement of workers from poorer areas to regions with better sanitation. This intriguing perspective suggests that better sanitation may coincide with increased human mobility, which could lead to the spread of dengue. However, this hypothesis has not been conclusively proven. Supporting this view, a study from Mato Grosso do Sul explained that good sanitation can reduce dengue cases, its effectiveness is significantly enhanced when accompanied by lower rainfall levels (Oliveira et al. 2023). This highlights the complex interplay of environmental, social, and infrastructural factors in influencing dengue transmission. It should be noted that our finding does not discourage multi-stakeholder effort to support adequate sanitation facilities provision.

In contrast, this study highlights the importance of a proper maintenance of sanitation infrastructure. According to Gibb et al. (2023), access to a proper sanitation infrastructure can decrease the dengue transmission risks, however, without careful maintenance, these facilities can become the breeding ground for mosquitoes. Based on *Bappenas*[1] and UNICEF (2024), while Indonesia has seen a positive trend in improved sanitation access with (80.92 percent) of the population, only 10.16% of the population has access to safe sanitation. This report also highlights that majority of Indonesian households have septic tanks that are not properly sealed, potentially leading to environmental and public health threats. This condition is also closely link to the dengue fever risks, as previous studies have established a strong association between the presence of *Aedes aegypti* mosquitoes and faulty septic tanks (Almeida et al. 2020; Sharp et al. 2023). On the other hand, the involvement of NGOs in WASH (Water, Sanitation, and Hygiene) programs in the eastern part of Indonesia, particularly in very remote areas, has made a significant positive impact on the local health conditions (Soeters et al. 2021; Susilo et al. 2020). These initiatives not only address the immediate sanitation needs, but also focus target schools, providing long-term health benefits for future generations (Karon et al. 2017). Therefore, there is a need for the government, NGO, and private sectors together to escalate the installation of safe sanitation infrastructure across provinces.

Moreover, our study found that the GDP per capita has a significant and positive influence on dengue fever infection. This result is inconsistent with previous studies which typically report a negative correlation between GDP per capita and dengue fever risks (Qi et al. 2015; Rodrigues et al. 2016). These earlier studies suggested that lower economic conditions are associated with higher dengue fever. However, it is important to consider alternative perspectives when analyzing the relationship between economic status and dengue. (Mulligan et al. 2015) pointed out that poverty does not necessarily correlate with higher dengue cases, emphasizing that dengue is not confined to low-income areas. Moreover, Yue et al. (2018) demonstrate the positive correlation between economic conditions and dengue fever incidence, arguing that improved economic condition can lead to increase population mobility, which in turn, raises the risk of dengue transmission. This argument is further supported by recent studies linking human mobility to the spread of dengue (Enduri & Jolad 2018; Falcón-Lezama et al. 2016; Johansen et al. 2021). Therefore, the relationship between economic status and dengue fever is multifaceted and may vary depending on regional dynamics.

[1] The Indonesia Ministry of National Development Planning.

Varying Implication of Gini Ratio and Government Health Spending on Dengue Fever Incidence

Another socioeconomic factors, Gini ratio and government spending on health, plays a complex role in influencing dengue fever cases across provinces. Gini ratio, as an indicator of economic inequality is expected to have a positive correlation with dengue fever incidence. Our study demonstrate that Gini ratio is positively associated with dengue risks in most areas, aligning with the previous studies (Gomes et al. 2023; Rodrigues et al. 2016; Teixeira & Cruz 2011). However, our estimation also shows an inverse correlation between Gini ratio and dengue cases in Papua and West Papua provinces (Fig. 4). According to Da Conceição Araújo et al. (2020), this anomaly can be explained by the extreme poverty and lack of sanitation infrastructure in these regions (Carabali et al. 2022). In areas with severe economic inequality, the lack of access to basic services may limit the ability to manage and mitigate dengue fever effectively, leading to distinct epidemiological patterns compared to other regions with relatively better socioeconomic conditions. These findings, again, demonstrate that dengue fever does not exclusively affect low socioeconomic groups. In contrast, our results emphasize the need for improved control and prevention measures for all socioeconomic classes across different regions. This suggests that effective dengue management must be comprehensive, addressing the unique needs and conditions of both affluent and disadvantaged areas to improvement in dengue fever control and prevention for every socioeconomic class in each region.

On the other hand, the government spending on health also expected to reduce the dengue cases number in a region. The findings show that public health spending significantly lowers the dengue incident in Central Java and Yogyakarta provinces. According to Prasetyo et al. (2018), Pratiwi et al. (2021), and Sambodo et al. (2021), Java Island has the highest number of national healthcare insurance claims compared to the eastern part of Indonesia. Simultaneously, our study shows that public health spending can exacerbate denge infections in regions where higher levels of corruption may exist (Benini Duarte et al. 2019; Massuda et al. 2018; Patel et al. 2015). An interesting argument regarding the eastern part of Indonesia is that, despite the implementation of special autonomy policy since 2001, health and education systems remain underdeveloped. This has perpetuated a cycle of poverty, leading to poorer health and education outcomes (Cahyaningsih & Fitrady 2019; Ishida et al. 2022).This result provides an insight that higher health spending does not necessary translated to better health outcome. Seposo et al. (2023) emphasize the critical importance of government quality and efficient resource allocation to ensure that the public health spending effectively enhance health outcomes.

Metrological Indicators of Dengue Fever Incidence Across the Nation

The metrological factors have a distinguished feature to affect dengue fever cases. Our estimation shows that the temperature has a positive association with dengue fever infection. This finding aligns with several studies, which have shown that higher temperature can increase dengue incidence (Choi et al. 2016; Damtew et al. 2023; Jain et al. 2019; Teurlai et al. 2015; Wu et al. 2009). Temperature is a critical factor in dengue fever transmission as it affects the mosquito life cycle, influencing population dynamics and the potential risks of dengue infection (Liu et al. 2023).

The precipitation shows a negative correlation with dengue infection, aligning with findings from previous studies (such as Faruk et al. 2022; Yuan et al. 2020). While moderate rainfall typically increases dengue incidents, by creating additional breeding sites for mosquitos, a heavy rainfall can disrupt mosquitos populations. This disruption occurs as immature mosquitoes, such as larvae and pupae, are washed away from breeding sites (Choi et al. 2016), ultimately reducing the incidence of dengue fever infections.

Lastly, this research displays a positive relationship between humidity and dengue fever cases. This finding is supported the previous studies that have empirically demonstrated that higher humidity levels increase dengue fever incident (Faruk et al. 2022; Monintja et al. 2021). The higher humidity extends mosquito lifespans, enhance daily biting rates, and improve female mosquitos' reproductive capabilities (Cui et al. 2021; Polwiang 2020).

Conclusion

Concluding Remarks

The study first highlights that increased population density contributes to a rise in the dengue cases across Indonesia, particularly in eastern regions where households often live in densely crowded conditions. Furthermore, improved access to sanitation is positively correlated with dengue fever cases incidence, suggesting that inadequate maintenance of sanitation infrastructure may create breeding grounds for mosquito. Additionally, GDP per capita is found to have a significant positive influence on dengue infections, indicating that higher economic status may increase population mobility, thereby elevating the risk of dengue transmission.

Second, the Gini ratio and government spending on health exhibit varying effects on for dengue fever incidence across the regions. While the Gini ratio generally shows a positive correlation with dengue risks, it exhibits an inverse relationship in Papua and West Papua, suggesting that dengue transmission is not confined solely to areas with low socioeconomic status. Additionally, public health spending appears to reduce dengue cases in some regions but its effectiveness varies across provinces, highlighting the importance of efficient resource allocation and governance to enhance the impact of health interventions.

Third, meteorological factors, particularly higher temperatures, are positively correlated with increased dengue incidence, while heavy rainfall may reduce it by disrupting mosquito breeding sites. Humidity, in particular, plays a crucial role, as it enhances mosquito lifespan, biting rates, and reproductive capabilities, thus contributing to higher dengue transmission. These findings highlight the complex interplay of socioeconomic and environmental factors in driving dengue fever incidence, emphasizing the need for region-specific strategies that address both environmental conditions and socioeconomic contexts for more effective control and prevention.

Policy Recommendation

To address poor sanitation practices contributing to dengue outbreaks, a comprehensive strategy is essential. Several non-physical interventions can be implemented by the government to tackle this issue. First, raising awareness and fostering community engagement are crucial. Educational campaigns, mobile apps, and local partnerships can empower communities to actively maintain clean environments and prevent mosquito breeding. Second, community-based waste management programs should be introduced to promote proper disposal of garbage, including used cans and containers that can collect water. Providing accessible garbage collection points and promoting recycling initiatives will support this effort. Additionally, local monitoring teams can be established to regularly inspect households, provide guidance on hygiene and sanitation practices, and encourage sustainable behavioral changes. By integrating these actions, the breeding grounds for *Aedes* mosquitoes can be significantly reduced, minimizing the risk of dengue transmission.

Furthermore, various government actions aimed at improving physical infrastructure and providing prevention equipment are essential to addressing the lack of access to proper sanitation. First, drainage systems should be repaired and upgraded to ensure efficient water flow and reduce the accumulation of standing water in residential areas, which creates breeding grounds for mosquitoes. Additionally, collaborating with local authorities to distribute essential tools—such as water container covers, mosquito nets, and larvicides—especially in high-risk communities, will significantly enhance dengue prevention efforts. Moreover, addressing population density and improving housing conditions, including access to proper sanitation, are crucial for promoting overall well-being and creating a healthy living environment. Housing improvement programs should prioritize densely populated areas and vulnerable households, particularly in eastern Indonesia, where overcrowding heightens the risk of dengue transmission.

Another recommendation, economic growth-related interventions are essential, as higher GDP per capita is associated with increased population mobility, which elevates dengue risks. Public health strategies should prioritize high-mobility groups by promoting personal preventive measures and implementing integrated vector management. Addressing economic inequality through inclusive health policies is equally critical. Community-based dengue prevention programs, such as "Satu Rumah Satu Jumantik," should be expanded to underserved areas to ensure interventions benefit all socioeconomic groups. Linking poverty alleviation with dengue prevention can further support low-income households by providing essential tools like mosquito nets and repellents.

Last but not least, optimizing health spending and governance is vital. Efforts should be focused on region-specific, cost-effective interventions, supported by transparent monitoring to ensure equitable resource allocation. Incorporating meteorological factors into dengue control strategies is also crucial. Early warning systems based on temperature, humidity, and rainfall can guide timely interventions, such as fogging or larviciding. Collaboration with meteorological agencies can strengthen outbreak preparedness and enhance response efficiency.

This methodology can be adopted by other countries that have macro-level data on dengue fever and relevant control variables available at the regional or provincial level. Countries particularly vulnerable to dengue fever, especially those with tropical and subtropical climates ideal for the breeding of *Aedes* mosquitoes—the primary vectors of the virus—include India, Brazil, Thailand, Bangladesh, Sri Lanka, and others. The approach would be especially valuable in countries with diverse geographical conditions, such as those consisting of multiple islands or varied landscapes. By applying this method, which includes GWR estimation for each province, more precise and localized results can be obtained, making it an effective tool for informing targeted interventions and improving dengue control efforts in such contexts.

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Declarations

Competing interests The authors declare no competing interests.

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