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Spatio-temporal analysis of dengue virus infection in the Bobonaro Municipality (2022-2024): insight from demographics and risk

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Abstract

Purpose: This study aimed to analyze the spatio-temporal patterns of dengue virus infection via kernel density estimation to assess the relative risk distribution and identify transmission hotspots in the Bobonaro municipality. **Methods:** A retrospective analysis was conducted on confirmed dengue cases (n=311) reported from seven community health centers and one referral hospital in Bobonaro from January 2022 to December 2024. Kernel density estimation with optimal bandwidth selection was employed to map the relative risk distributions and identify spatial clusters. Demographic patterns across age categories were analyzed using negative binomial regression with a quadratic age-rank term, and sex distribution was analyzed using an exact two-proportion binomial test. **Results:** Annual dengue cases increased by 41.48% over the study period, with significant seasonal patterns observed during the dry and rainy seasons. Case counts increased from the infancy category toward a peak in the youth category (5–14 years, 158 cases, 50.8% of all cases) before declining in older age groups, a pattern confirmed by negative binomial regression with a quadratic age-rank term (incidence rate ratio [IRR] 8.45, 95% CI 2.70–25.37, p<0.001 for the linear term and 0.74, 95% CI 0.65–0.85, p<0.001 for the quadratic term). Females accounted for a slightly higher proportion of cases (51.8%, n=161) than males (48.2%, n=150), a difference that was not statistically significant (p= 0.571). Spatial analysis revealed persistent hotspots in southeastern Bobonaro, with new clusters emerging in the northern regions by 2023 and transmission typically contained within an 80 m radius. **Conclusion:** This study identified clear demographic vulnerabilities and dynamic spatial patterns of dengue transmission in Bobonaro, demonstrating the utility of GIS-based spatial analysis for strengthening surveillance and guiding targeted vector control in resource-constrained settings.

Keywords: communicable disease transmission; dengue; geographic information systems; global health; spatial analysis

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INTRODUCTION

Dengue fever remains the most significant mosquito-borne viral disease affecting humans globally, driven by four distinct dengue virus (DENV) serotypes. It imposes substantial economic and healthcare burdens in resource-limited settings [1–4]. In Timor-Leste, dengue has been a major public health concern since the first outbreak in Dili in 2005, and the disease is now present across all 13 municipalities, including the Oecusse Ambeno Special Autonomy Region [5,6]. Approximately 60% of the national population resides in DENV-endemic areas, and surveillance data from 2022 recorded 1,286 confirmed infections, with a case fatality rate of 1.6% [6,7].

Bobonaro, located at the western end of Timor-Leste, historically reported only 55 dengue cases with no fatalities; however, it emerged as the second-highest dengue-affected municipality after Dili in the first trimester of 2024, with 83 cases, two deaths, and an incidence rate of 1 per 1,000 population [6]. The reliance on passive surveillance in Timor-Leste, constrained by limited clinical and laboratory capacity, likely results in underreporting and obscures the true burden of disease [6,8–10].

Geographic information system (GIS) methodology, widely used to assess and visualize infectious disease risk, including visceral leishmaniasis, malaria, and dengue [11–19], offers a practical framework for strengthening surveillance under resource constraints. Spatial autocorrelation and cluster analyses have identified dengue hotspots and supported targeted vector control in hyperendemic settings, such as Venezuela, India, and Singapore [12,20–24]. A previous study estimated dengue incidence risk across Timor-Leste as a whole [13,25]; however, Bobonaro, a considerably smaller municipality (167.29 km^2 versus 15,007 km^2 nationally), may exhibit distinct transmission dynamics driven by localized human movement.

Spatial-temporal analysis of dengue is complicated by geographic context uncertainty and reporting delay bias [26,27]. To address these constraints, this study applied kernel density estimation (KDE), a nonparametric method for estimating disease intensity from finite case data [28–34], to analyze the spatiotemporal patterns of dengue virus infection, assess relative risk distribution, and identify transmission hotspots in the Bobonaro municipality, providing actionable evidence for targeted vector control and early warning strategies [6,35–37]. This study aimed to analyze the spatiotemporal patterns of dengue virus infection via kernel density estimation to assess the relative risk distribution and identify transmission hotspots in the Bobonaro municipality. This study offers actionable insights for policymakers to direct vector eradication efforts, plan outbreak prevention strategies, and disseminate early warning information to communities, ultimately reducing dengue risk in the region.

METHODS

Study design

This study employed a retrospective design to analyze dengue surveillance data from January 2022 to December 2024 [38]. The population-at-risk denominator used in the relative risk formula (Equation 6) was explicitly attributed to the Bobonaro Health Service Statistics 2022 report, stated directly beneath the equation [39,40]. The research framework incorporated both temporal and spatial analyses to assess dengue distribution patterns and the relative risk across the Bobonaro municipality of Timor-Leste.

Study area and setting

Bobonaro municipality, located in the western region of Timor-Leste, covers a surface area of 1,380.8 square kilometers (km^2). According to the preliminary results of the 2022 Population and Housing Census, the municipality has a total population of 106,543, which is distributed across six administrative posts (sub-districts), 50 villages, and 194 subvillages [39,40] (Figure 1). Geographically, Bobonaro is bordered by Liquiça municipality to the north, Covalima municipality to the south, Ermera and Ainaro municipalities to the east, and Atambua, Indonesia, to the west [40]. This geographic diversity and population distribution make Bobonaro a critical area for studying dengue transmission dynamics.

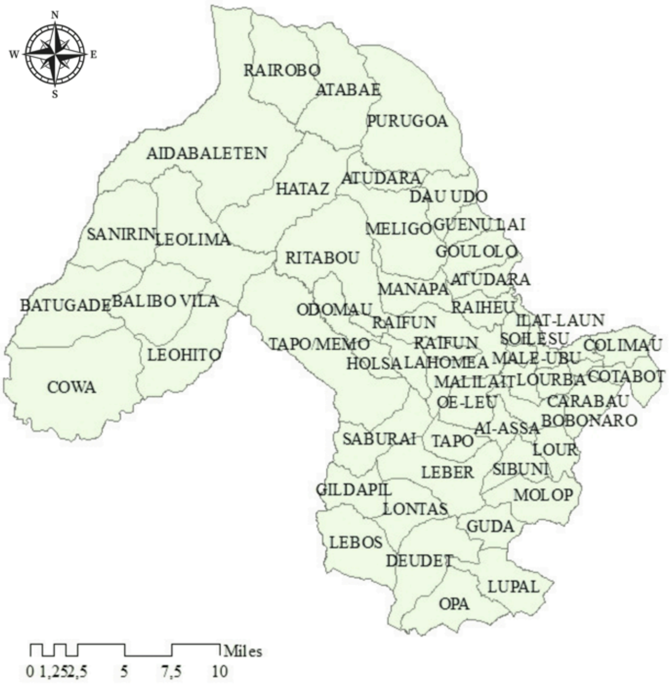


Figure 1. The administrative boundaries maps of Bobonaro Municipality

Data collection

Monthly reports of diagnosed dengue cases were collected from seven community health centers (CHCs) and one referral hospital in the Bobonaro municipality (Maliana referral hospital (HRM)). These reports were sourced from the Dengue Disease Surveillance database maintained by the Bobonaro City

Health Office (SMS Bobonaro) and spanned the period from January 2022 to December 2024. Dengue cases were classified into three categories based on clinical symptoms and laboratory results: hemoglobin (Hb) levels, leukocyte (white blood cell) counts, thrombocyte (platelet) counts, hematocrit (Ht) levels, and non-structural protein 1 (NS1) detection. Additional confirmatory tests included rapid diagnostic tests (NS1, IgM, and IgG) and polymerase chain reaction (PCR) assays for serotypes DENV-1, DENV-2, DENV-3, and DENV-4. The categories were defined as mild, moderate, and severe dengue. Case classification was established based on a positive dengue rapid diagnostic test, together with clinical assessment by the attending physician at the reporting health facility, following the WHO dengue classification framework [41].

This investigation encompassed all confirmed dengue cases within the specified categories. The demographic profile of each patient comprised age, gender, residential address, date of confirmed diagnosis, and hospital information. To ensure privacy, the data were anonymized, and infections were assumed to have occurred at the patients' residences. The population size data for the 50 villages in Bobonaro from 2022 to 2024 were obtained from the Bobonaro Health Service Statistics for 2022 [40]. The data were further stratified by age group (Table 1). The comparison of case counts across age categories was analyzed using negative binomial regression with a quadratic age-rank term, selected after Poisson regression demonstrated significant overdispersion [42]. Comparison between sexes was analyzed using an exact two-proportion binomial test using RStudio Version 2025.09.2 by Posit Software, PBC.

Table 1. Age groups of dengue patients

Age (years old)	Category
Less than 1	Infancy
1- 4	Preschool
5- 14	Youth
15-24	Young adulthood
25-39	Middle adulthood
40-59	Older adulthood
≥ 60	Retirement

Kernel density estimation for relative risk

To estimate the continuous spatial distribution of the relative risk of dengue incidence, we employed the kernel smoothing method [43]. This approach calculates the probability of dengue cases occurring during outbreak periods based on the spatial distribution of cases (patient residential addresses) and the temporal distribution of reported cases in Bobonaro. Let $f(z)$ represent the spatial density function of dengue cases and $g\ (z)$ represent the temporal density function of the infected population in specific regions. The relative risk of dengue at spatial coordinate $\vec{z}$ within Bobonaro (W) is defined as:

$$\vec{z}(\tfrac{x}{y})\epsilon W \text{ (W is Bobonaro) can be defined as: } r\left(\vec{z}\right) = \frac{f(\vec{z})}{g(\vec{z})} \quad (1)$$

Suppose that $\vec{di}$ and $\vec{pj}$ represent the spatial coordinates of the i-th dengue case and the j-th individual, respectively. Let m and n i denote the number of dengue cases and the total population in a given year, respectively. The density functions f f and g g can be approximated as:

$$f\left(\vec{z}\right) \approx \hat{f}\left(\vec{z}\right) = \frac{1}{m}\sum_{i=1}^{m} Kh(\vec{z} - \vec{di}) \quad (2)$$

$$g\left(\vec{z}\right) \approx \hat{g}(\vec{z}) = \frac{1}{n}\sum_{j=1}^{n} Kh(\vec{z}\ \vec{pj}) \quad (3)$$

A variable bandwidth selector was used for the multivariate kernel density estimation [44], represented by the following equation:

$$kh\left(\vec{w}\right) = \frac{1}{hx\,hy} K\left(\frac{\vec{w}}{h}\right) = \frac{1}{hx\,hy}\frac{1}{2\pi}\ exp(\frac{-1}{2}\vec{w}\,T\left(\begin{pmatrix} hx & 0 \\ 0 & hy\end{pmatrix}^{-1}\right) 2 \to \vec{w})$$

(4) where $\begin{pmatrix} hx & 0 \\ 0 & hy\end{pmatrix}$ is the scaled bandwidth.

The optimal bandwidth was determined via normal smoothing, which minimizes the asymptotic mean integrated squared error (AMISE) [32,45]. This value was calculated using the normal scale (NS) function in ArcGIS Pro® 10.8 for Windows. Normal smoothing provided asymptotically optimal fixed bandwidths for spatial and spatiotemporal normal densities, enabling precise estimation of dengue incidence for each observation year in the study period.

This study used secondary data approved by the Municipal Health Services Directorate of Bobonaro, Maliana City, Timor-Leste. The study was approved by the Ethics Committee of the SMS Bobonaro (approval number 658/DSMSB/XI/2024). All patient identities were kept confidential to ensure privacy and compliance with the ethical standards.

RESULTS

Dengue cases

A total of 311 hospitalized dengue cases were recorded from January 2022 to December 2024, reflecting an annual increase of 41.48% (Figure 2). The temporal distribution of cases revealed distinct seasonal patterns. In 2022 and 2024, the peak incidence occurred between January and April, coinciding with the dry season, whereas a secondary peak was observed in June of 2024 (Figure 3). In contrast, 2023 exhibited a bimodal distribution, with peaks during both rainy and dry seasons. The observed patterns suggest that dengue transmission in Bobonaro is influenced by both intrinsic (e.g., vector density and human mobility) and extrinsic (e.g., rainfall and temperature) factors.

Age and gender distributions of dengue patients

The age distribution of dengue cases showed a consistent pattern over the three years of observation (2022–2024). Figure 4 illustrates the age and sex distributions of dengue cases, highlighting the predominance of infections in younger age groups. Specifically, the 5–14 years age group presented the greatest number of cases, followed by the 1–4 years age group. On average, 43.4% of the total patients (135 of 311 cases) were aged under 10 years. In contrast, the number of cases among older adults (≥ 25 years) was significantly lower, with decreases in the 40–59 and ≥ 60 years age groups. This pattern underscores the vulnerability of children to dengue infection in Bobonaro. The number of cases increased from the infancy category toward a peak in the youth category (5–14 years, 158 cases, 50.8% of all cases), before declining in older age groups (Table 2, Figure 4). This pattern was confirmed by negative binomial regression with a quadratic age-rank term, yielding an incidence rate ratio (IRR) of 8.45 (95% CI 2.70–25.37, $p<0.001$) for the linear term and 0.74 (95% CI 0.65–0.85, $p<0.001$) for the quadratic term, indicating a peaked rather than a monotonically decreasing distribution across the age spectrum. This pattern is consistent with heightened susceptibility among school-aged children due to immunological and exposure-related factors, underscoring the value of school-based vector control interventions in high-incidence residential areas. Female patients accounted for 51.8% (n=161) and male patients 48.2% (n=150) of the total 311 cases over the three years. This difference was not statistically significant (exact binomial test, $p = 0.571$), indicating that sex is not a major determinant of susceptibility to dengue in this population.

Dengue risk estimation and spatial representation

Following the calculation of normal smoothing, the optimal bandwidth for each observation year was determined (Table 3). These bandwidth values were subsequently used to estimate the dengue relative risk and generate spatial risk maps. The spatial distribution of dengue risk in Bobonaro remained relatively consistent between 2022 and 2024, with high-risk villages predominantly concentrated in the southern and southeastern regions of the municipality (Figure 5). In contrast, low-risk villages were located primarily in the western and northeastern regions. However, a notable shift occurred in 2023 with the emergence of a new disease hotspot in the northern Bobonaro region. Despite this change, most hotspots remained concentrated in the southeastern regions during the study period.

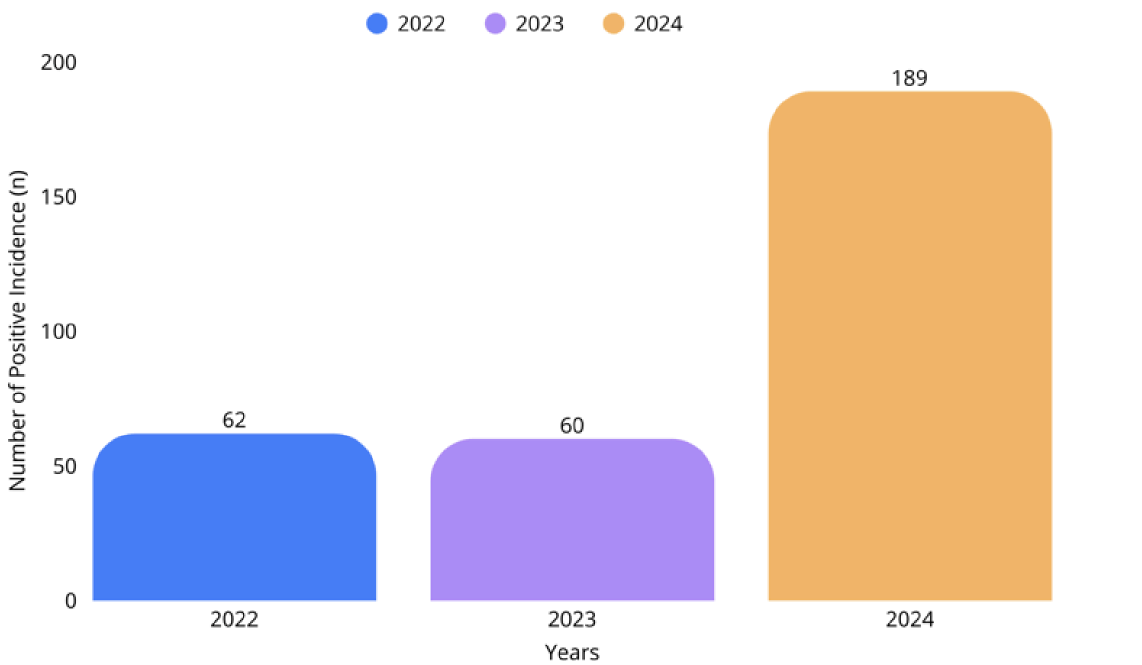


Figure 2. Number of dengue cases reported from seven CHCs and one HRM in Bobonaro from 2022 to 2024

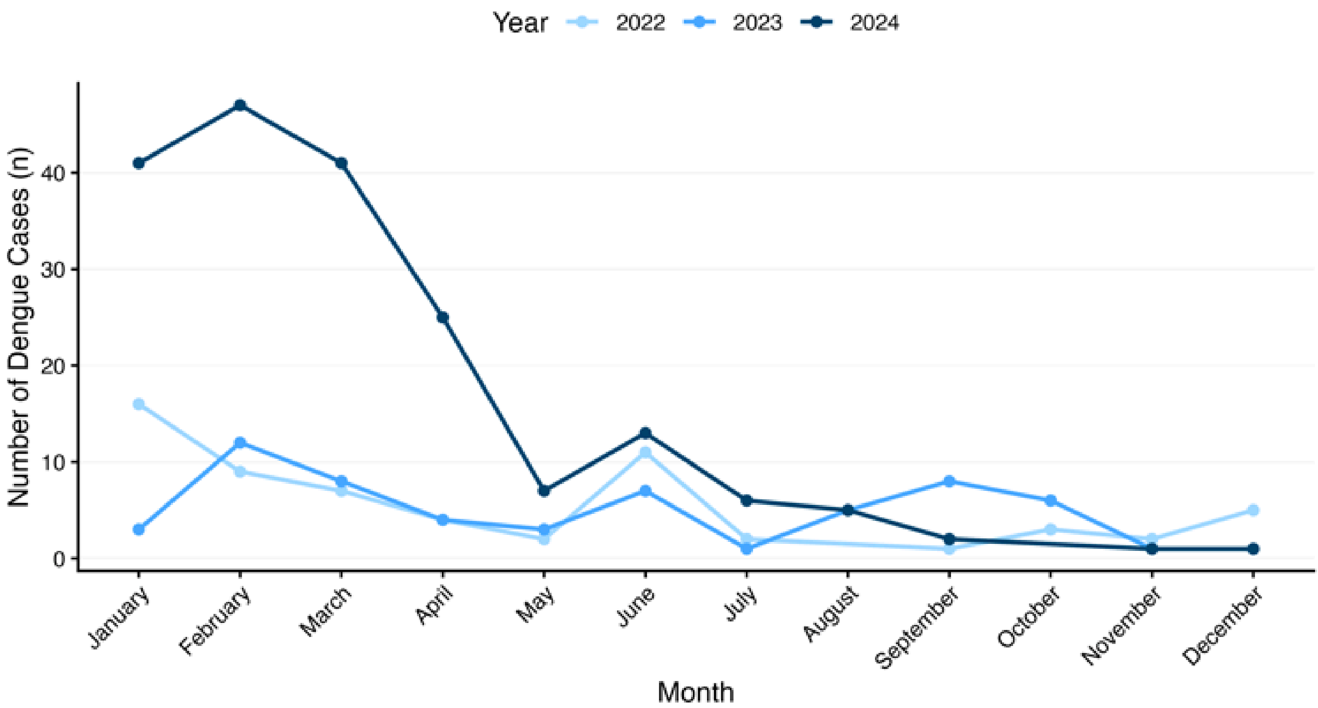
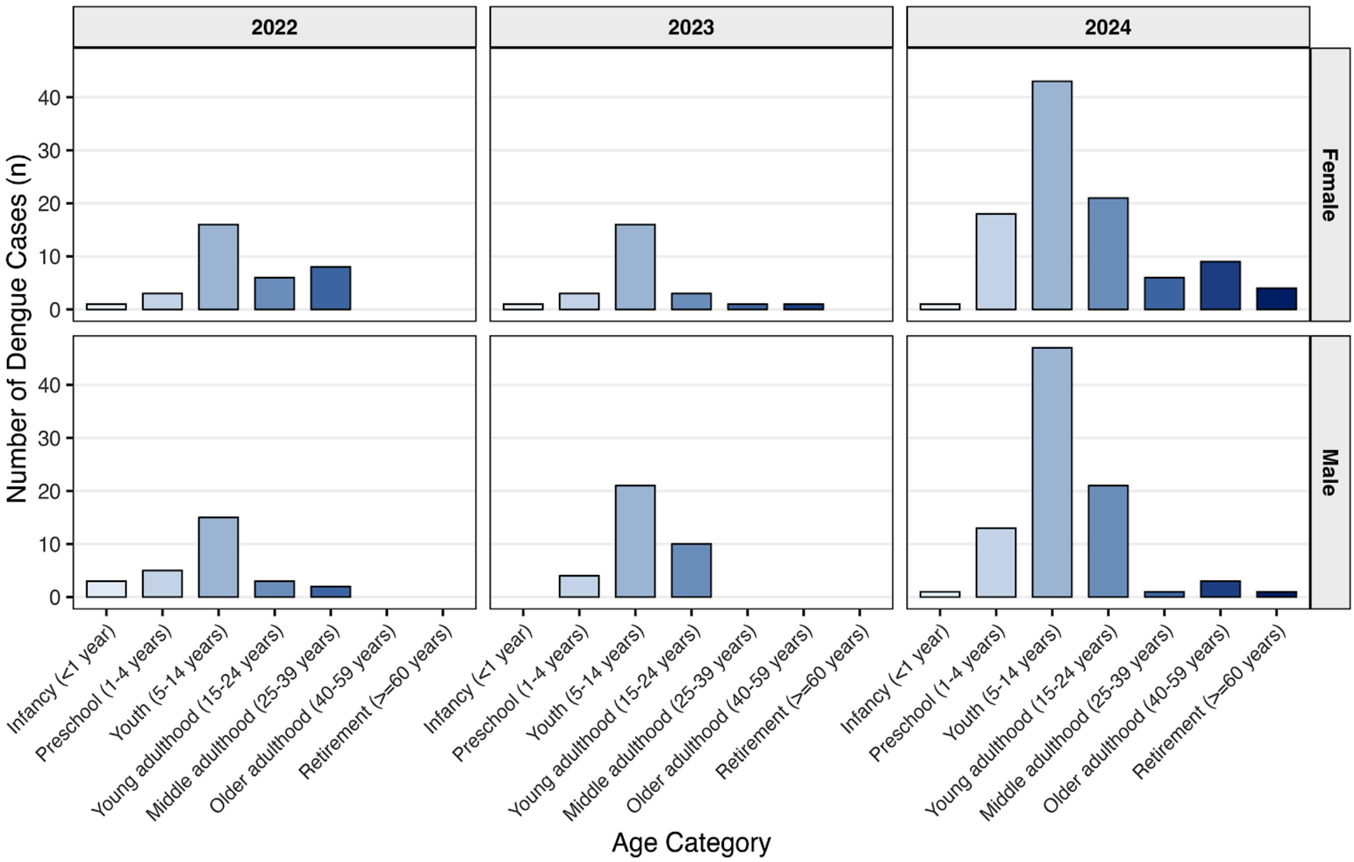


Figure 3. Monthly dengue cases reported from seven CHCs and one HRM in Bobonaro from 2022 to 2024



Notes: Bar color reflects a sequential light-to-dark blue gradient following the seven age categories in Table 1, with panels separated by sex (rows) and year (columns).

Figure 4. Distribution of dengue cases in Bobonaro by age category, sex, and year, 2022–2024

Table 2. Distribution of dengue cases in Bobonaro municipality by age category and sex, 2022- 2024 (n = 311)

Age category (Table 1)	2022 (n)	2023 (n)	2024 (n)	Total (n)	Total (%)	Female (n)	Male (n)
Infancy (<1 year)	4	1	2	7	2.3	3	4
Preschool (1-4 years)	8	7	31	46	14.8	24	22
Youth (5-14 years)	31	37	90	158	50.8	75	83
Young adulthood (15-24 years)	9	13	42	64	20.6	30	34
Middle adulthood (25-39 years)	10	1	7	18	5.8	15	3
Older adulthood (40-59 years)	0	1	12	13	4.2	10	3
Retirement (≥60 years)	0	0	5	5	1.6	4	1
Total	**62**	**60**	**189**	**311**	**100.0**	**161**	**150**

Remarks: Age categories follow the classification presented in Table 1. The statistical details underlying this table, including the test methods, incidence rate ratios, and confidence intervals, are reported in the accompanying results text.

Table 3. Bandwidth values under normal smoothing

Normal smoothing	
Dengue cases 2022	$h = 15.769\,m$
Dengue cases 2023	$h = 13.611\,m$
Dengue cases 2024	$h = 63.685\,m$

The relative risk of dengue was estimated using the following formula:

$$\theta it = \frac{yit}{Eit};\ i = 1, \ldots, 30 \text{ and } t = 2022,\ 2023,\ 2024 \qquad (5)$$

where θit, yit and Eit represents the observed number of cases and the expected number of cases in area i and time t, respectively. The expected of cases Eit was calculated as:

$$Eit = Nit \frac{\sum_{i=1}^{n}\sum_{t=1}^{T} yit/nT}{\sum_{i=1}^{n}\sum_{t=1}^{T} Nit/nT} \qquad (6)$$

where Nit represents the population at risk in area i at time t. This formulation accounts for variations in population density, ensuring that the relative risk estimates reflect true epidemiological patterns rather than demographic biases. The population-at-risk denominator used in Equation 6 was obtained from the Bobonaro Health Service Statistics 2022 report published by the Directorate of Regional and Municipal Statistics. The normal kernel density approach was employed to estimate the relative risk, with the optimal bandwidth determined by minimizing the asymptotic mean integrated squared error (AMISE). This method provides a robust framework for identifying spatial clusters of dengue incidence and mapping their distribution over time.

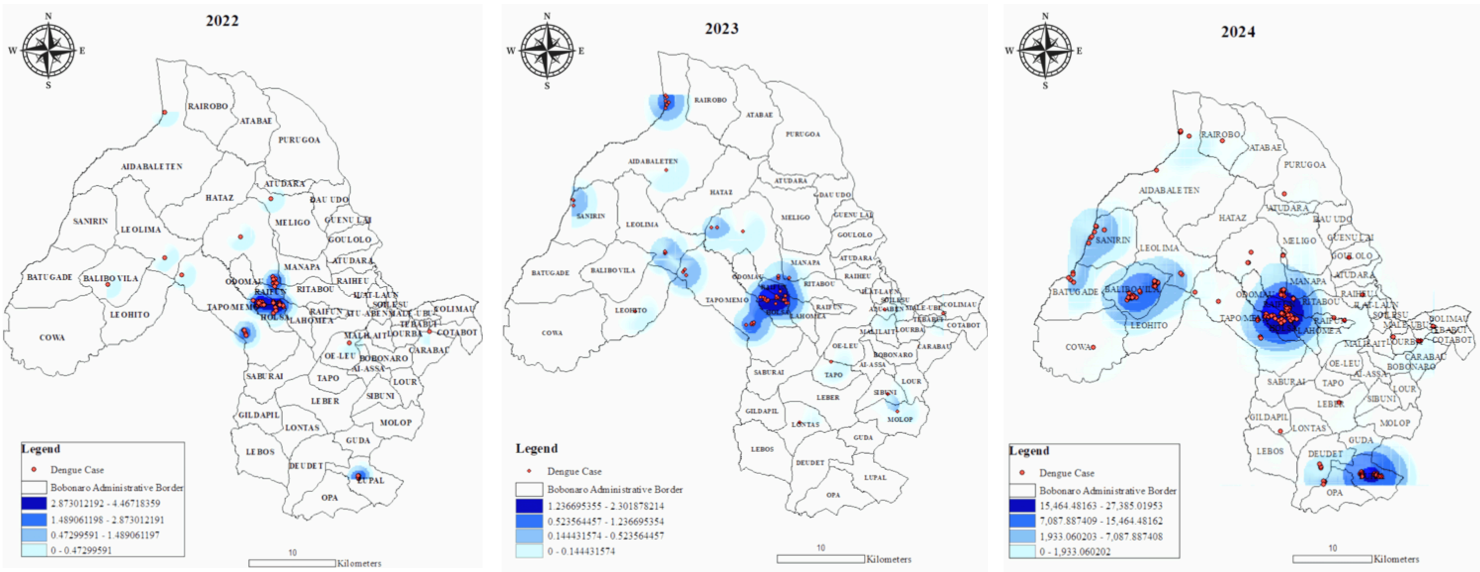


Figure 5. Spatial analysis of the relative risk of dengue in Bobonaro at the village (Suco) level in 2022 – 2024

DISCUSSION

The incidence of dengue in Bobonaro increased markedly from 2022 to 2024, with a distinct seasonal pattern characterized by a surge in cases during the early months of the year, peaking between January and April each year. This trend closely aligns with meteorological factors,particularly rainfall and humidity, which have been consistently identified as key drivers of dengue transmission. The bimodal incidence pattern observed in 2023 is consistent with prolonged rainfall creating favorable breeding conditions for Aedes mosquitoes, followed by a secondary resurgence during the dry season attributable to household water storage practices [46]. These findings are corroborated by data at multiple scales, including village-level observations (Faridah, unpublished data), regional analyses [47], and nationwide studies in Timor-Leste [6,13]. Notably, while temperature variations have been shown to influence dengue dynamics in some regions, their impact on Bobonaro appears negligible, a phenomenon also observed in other tropical settings [13,48]. This underscores the importance of localized climatic factors in shaping dengue transmission patterns [49].

Our study revealed a greater prevalence of dengue in females than in males, a trend potentially attributable to sex-specific behavioral and biological factors. Females are more likely to engage in domestic activities, increasing their exposure to Aedes mosquitoes. This pattern is also consistent with sex-disaggregated dengue surveillance findings in the Lao People's Democratic Republic [50] and across several dengue-endemic countries in Asia [51]. Biologically, sex-based differences in innate and adaptive immune responses have been shown to modulate susceptibility and clinical outcomes across a broad range of viral infections [52], offering an additional physiological explanation for the pattern observed in this study. This finding is consistent with a previous study in Timor-Leste [25]. Additionally, sex-based differences in susceptibility to dengue serotypes may play a role. For example, Chang et al. reported that males are more prone to DENV-1 infection, whereas females are more frequently affected by DENV-3 [53].

In Timor-Leste, DENV-3 was the predominant serotype during the 2005 outbreak [5,6], which may partially explain the higher incidence among females in our study. Surveillance reporting in Timor-Leste has consistently identified DENV-3 as a circulating serotype, consistent with the 2005 outbreak findings. This continuity strengthens the plausibility that primary DENV-3 infection among children, who are typically immunologically naive to dengue, contributes to the elevated case burden observed in the Youth category in this study, in line with a meta-analysis linking primary DENV-3 infection to a higher proportion of severe dengue [54]. However, our data lack serotype-specific information, highlighting the need for further research to elucidate the interplay between sex, serotype distribution, and dengue incidence in Bobonaro. The study also identified children under 10 years of age as the most vulnerable demographic, with a significant increase in cases by 2024. This aligns with findings from other regions, such as the Philippines and Brazil, where age-related immune responses have been implicated in dengue susceptibility [55]. The consistency of this pattern across Timor-Leste suggests that children are a critical target group for dengue prevention and control efforts.

The consistency of hotspots in the southeastern regions suggests that persistent environmental or socioeconomic factors drive dengue transmission in these areas. The emergence of a new hotspot in northern Bobonaro in 2023 may reflect changes in vector habitats, human mobility, or climatic conditions, which warrants further investigation. Spatial analysis revealed a clustered distribution of dengue cases, with high-risk areas concentrated in Bobonaro's downtown region, particularly at the intersection of Holsa, Odomau, Tapo Meomo, and Raifun villages within the Maliana administrative post area (Figure 5). This area is characterized by high economic activity, dense population growth, and the concentration of public services, commercial enterprises, and recreational facilities [40]. These factors, coupled with urbanization, create an environment conducive to dengue transmission, as evidenced by similar patterns in other urbanized regions [6,56–58].

Kernel density estimation maps revealed the emergence of new hotspots in the northern, western, and southern parts of the city in 2023, with further expansion in 2024. This spatial shift may be linked to rapid urban development in these areas, which has attracted rural–urban migration and increased human mobility. For instance, the southern region borders Covalima, a municipality with a high dengue burden [6], while the western region, proximal to the Balibo Administrative post, functions as a crucial entry point between Timor-Leste and Indonesia's Nusa Tenggara Timur (NTT) province [39]. These observations are corroborated by studies conducted in Thailand [59] and Brazil [60], which emphasize the significance of human mobility in facilitating dengue transmission.

The spatial clustering of dengue cases in Bobonaro appears to be localized, with transmission dynamics driven primarily by short-distance human movement (< 1 km), as reported by Guzetta et al. [61]. This is consistent with research in Venezuela, where dengue infections were found to cluster within households and blocks within a radius of 20–110 m [21]. The heterogeneous nature of dengue transmission underscores the complex interplay between environmental, climatic, vector-related, and human behavioral factors [62–64]. Despite these insights, this study did not quantify precise fluctuations in cluster size over time, which may reflect inconsistencies in dengue reporting or program implementation. This limitation highlights the need for enhanced surveillance systems to improve data accuracy and ensure timely detection of emerging hotspots [13,65,66]. Additionally, the absence of dengue clusters in northeastern Bobonaro warrants further investigation, as it may indicate underreporting or unique ecological and demographic factors that influence the transmission dynamics in this area.

Implications for public health

The findings of this study have significant implications for public health, particularly in low-resource settings, such as Timor-Leste. The identification of dengue hotspots through spatiotemporal analysis offers a pragmatic solution for optimizing resource allocation and targeting vector control efforts in high-risk areas. This is especially critical in regions with limited healthcare infrastructure, where passive surveillance systems often fail to capture the dengue burden. The study's emphasis on localized risk assessment enables policymakers to design more effective and context-specific intervention strategies, such as community-based vector eradication programs and early warning systems. Furthermore, the demographic findings highlight the relatively high dengue prevalence among children and suggest the need for tailored public health campaigns that address these vulnerable groups. The integration of GIS technology into national surveillance systems can increase the accuracy of disease mapping and forecasting, facilitating timely responses to disease outbreaks. Embedding such spatial surveillance within a broader One Health framework, which integrates climatic, entomological, and human health data, has been proposed to strengthen the design and targeting of vector control programs [67]. Additionally, this study underscores the importance of addressing underreporting and strengthening data collection mechanisms to improve the reliability of epidemiological data. By leveraging spatial analysis, public health authorities can mitigate the immediate impact of dengue and build long-term resilience against future outbreaks.

The limitations of this study are that reliance on passive surveillance data from health facilities may underestimate the true burden of dengue in Bobonaro, as asymptomatic cases and individuals seeking traditional or self-medication remain undetected. The assumption that infection occurs at the patient's residence can lead to spatial bias, as transmission can occur at workplaces, schools, or other locations frequently visited by patients. In addition, the retrospective design of the study and its limited temporal scope limit our ability to identify long-term transmission patterns and cyclical trends. The absence of serotype-specific data and detailed vector surveillance information further limits our understanding of the complex virus–vector–host interactions that drive local transmission dynamics.Future research should address these limitations using several approaches. Prospective studies incorporating active surveillance, serological surveys, and movement tracking could provide more accurate estimates of the dengue burden and transmission patterns. Integrating environmental data, including microclimate variations, land use changes, and vector ecology, would enhance our understanding of spatiotemporal risk factors. Additionally, research exploring the socioeconomic determinants of dengue transmission, including housing conditions, water storage practices, and health-care-seeking behaviors, can inform more effective intervention strategies. The development of predictive models incorporating machine learning algorithms and real-time surveillance data can improve early warning systems and outbreak prediction capabilities in resource-limited settings, such as the Philippines.

CONCLUSION

This study provides compelling evidence for the dynamic spatiotemporal patterns of dengue transmission in the Bobonaro municipality of Timor-Leste through the application of kernel density estimation and a comprehensive epidemiological analysis. The identification of persistent hotspots in the southeastern regions, coupled with the emergence of new transmission clusters in the northern areas, demonstrates the evolving nature of dengue risk distribution. The disproportionate burden among children under 10 years of age and the slight predominance of female cases highlight critical demographic vulnerabilities that require targeted intervention. Our findings underscore the utility of GIS-based spatial analysis in resource-constrained settings, offering a practical framework for enhancing surveillance systems and optimizing public health response. The localized nature of transmission clusters, typically within an 80 m radius, suggests that targeted vector control and community-based prevention programs can effectively reduce the dengue burden in high-risk areas. These insights provide an evidence-based foundation for policymakers to implement more efficient and context-specific dengue control strategies in Timor-Leste and other resource-limited settings.

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Authors' contribution

Z.V.D.C. and I. M.D.M.A.: Conceptualization, Methodology, Writing—original draft, Formal analysis, Data curation, Writing—review & editing, Supervision, Funding acquisition. All authors approved the final manuscript.

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Data availability
The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethics statement
The study was approved by the Ethics Committee of the SMS Bobonaro (approval number 658/DSMSB/XI/2024). All patient identities were kept confidential to ensure privacy and compliance with the ethical standards.

Conflicts of interest
The author(s) declare(s) no conflict of interest regarding the publication of this manuscript.

Use of artificial intelligence (AI)
We confirm that no artificial intelligence (AI) tools or methodologies were utilized at any stage of this study, including during data collection, analysis, visualization, or manuscript preparation. All work presented in this study was conducted manually by the authors without the assistance of AI-based tools or systems.

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