Article

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Spatial Analysis of Predisposition to Dengue Hemorrhagic Fever (DHF) Incidence in Timor Tengah Utara Regency in 2020-2022

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Dengue Hemorrhagic Fever (DHF) is a potentially fatal infectious disease caused by the dengue virus, which is transmitted through the bites of Aedes aegypti and Aedes albopictus mosquitoes. In 2022, the Timor Tengah Utara Regency recorded 44 cases of DHF, with the highest incidence (31 cases) concentrated in the Sasi Public Health Center. Historical data revealed 56 cases in 2021, including one fatality, and 124 cases in 2020, with two deaths. This study aimed to analyze the influence of age, occupation, mobility, residence, income, and education on DHF incidence and examine the spatial distribution of DHF cases in the region using GeoDa software. Employing a descriptive-exploratory design, this study analyzed data from 224 patients with DHF. Bivariate LISA analysis revealed significant spatial autocorrelation for mobility ($p = 0.0000$), income ($p = 0.0061$), residence ($p = 0.0003$), and education ($p = 0.0000$), whereas age ($p = 0.2774$) and occupation ($p = 0.9260$) showed no significant relationships. Further testing with the Lagrange Multiplier (LM) model ($p = 0.0000$) confirmed spatial dependence, and the Spatial Autoregressive Model (SAR) was identified as the best model because of its highest R^2 (0.974420) and lowest AIC (329.606). These findings underscore the importance of considering spatial factors in DHF management and provide a foundation for targeted interventions, such as improving community awareness and resource allocation in high-risk areas. The results demonstrate the potential of spatial analysis tools to enhance public health strategies for infectious disease control.

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Public Interest Statement

This study investigated the spatial predisposition of Dengue Hemorrhagic Fever (DHF) in Timor Tengah Utara Regency during 2020–2022, revealing critical spatial dependencies influencing the distribution of the disease. By integrating advanced spatial analysis tools, such as GeoDa, this study identified key socio-demographic and environmental factors contributing to DHF cases. This study fills a significant gap in understanding the geographic and social determinants of DHF, providing evidence for targeted public health interventions. The findings offer practical insights for policymakers and health practitioners, aiding the development of effective prevention strategies to mitigate the burden of DHF in high-risk areas.

Introduction

Spatial epidemiology analyzes diseases within specific regions by considering environmental, behavioral, and sociodemographic risk factors of disease. According to Baker (Nur Aisyah et al., 2021), there are four study types: disease mapping, geographic correlation, cluster detection, and source point analysis. Spatial analysis examines location, distribution patterns, spatial interactions and regional differences. In public health, spatial approaches emphasize addressing health problems and priorities from a geographic perspective. Geographic Information Systems

(GIS) play a crucial role in health surveillance by providing spatial visualizations of health events and analyzing the relationships between location, environment, and disease. Tools like ArcGIS, QGIS, and GeoDa support this approach (Rohman et al., 2020)

GeoDa is software designed for spatial data exploration techniques, including descriptive analysis, spatial autocorrelation statistics, and spatial outlier detection. Compatible with ESRI files, GeoDa enables spatial regression analysis, such as Ordinary Least Squares (OLS), to identify the best regression model. In this study, GeoDa was used to facilitate the spatial regression analysis. Dengue Hemorrhagic Fever (DHF) is a potentially fatal infectious disease caused by the dengue virus, which is transmitted by Aedes aegypti and Aedes albopictus mosquitoes (Jayanti et al., 2017). These vectors thrive in water storage areas, stagnant water, and dark, humid environments (Zulheri et al., 2019)

Epidemiologically, Dengue Hemorrhagic Fever (DHF) is rapidly growing worldwide and remains a significant global health issue. DHF is transmitted by Aedes aegypti mosquitoes carrying the dengue virus and is characterized by sudden fever lasting 2–7 days, accompanied by restlessness, fatigue, epigastric pain, and bleeding signs such as petechiae, ecchymosis, or purpura. According to the Indonesian Ministry of Health, symptoms may also include nosebleeds, vomiting blood, bloody stools, decreased consciousness, or shock (Kemenkes, 2020)

According to Timreck (2002) the Epidemiological Triangle highlights the interactions between the environment, host, and agent as factors influencing disease. This concept analyzes the roles and interrelations of each factor in infectious disease epidemiology, including their influence, reactivity, and effects on each other. A person is considered healthy when these factors are in balance, whereas illness may result from weakened immunity, increased pathogenicity, or environmental changes. The Epidemiological Triangle highlights the interactions between the environment, host, and agent as factors influencing disease. This concept analyzes the roles and interrelations of each factor in infectious disease epidemiology, including their influence, reactivity, and effects on each other. A person is considered healthy when these factors are in balance, whereas illness may result from weakened immunity, increased pathogenicity, or environmental changes.

According to World Health Organization data (WHO, 2025) DHF accounts for 3.21% of the global population. In Indonesia, the Ministry of Health reported 17,820 cases in 2020. In East Nusa Tenggara (NTT) Province, 4,518 DHF cases and 48 deaths were recorded as of April 1, 2020. Timor Tengah Utara Regency is among the regions in NTT with a significant DHF burden, with cases spread across multiple districts from 2018 to 2022, ranking it among the higher-incidence areas in the province.

According to data from the local health office, the number of DHF cases in Timor Tengah Utara Regency reached 44 in 2022. These cases were reported across several health centers, with Puskesmas Sasi recording the highest number of (31 cases). In comparison, 2021 saw 56 cases with one fatality, while 2020 recorded 124 cases and two deaths. Factors influencing the increase and spread of DHF include host characteristics, environmental conditions (geography, rainfall, wind, humidity, and seasons), demographic factors (population density, mobility, behavior, and socioeconomic status), and the agent (Fatati et al., 2017; Zulheri et al., 2019). The density of mosquito vectors also plays a critical role in determining morbidity and mortality.

To address these challenges, the Timor Tengah Utara Health Office has implemented several mosquito eradication efforts (PSN), including epidemiological investigations, mosquito larvae inspections, fogging, the "3M Plus" movement (draining, covering, burying, and using larvicides), distributing fish to water containers, and other preventive measures aimed at reducing the mosquito population.

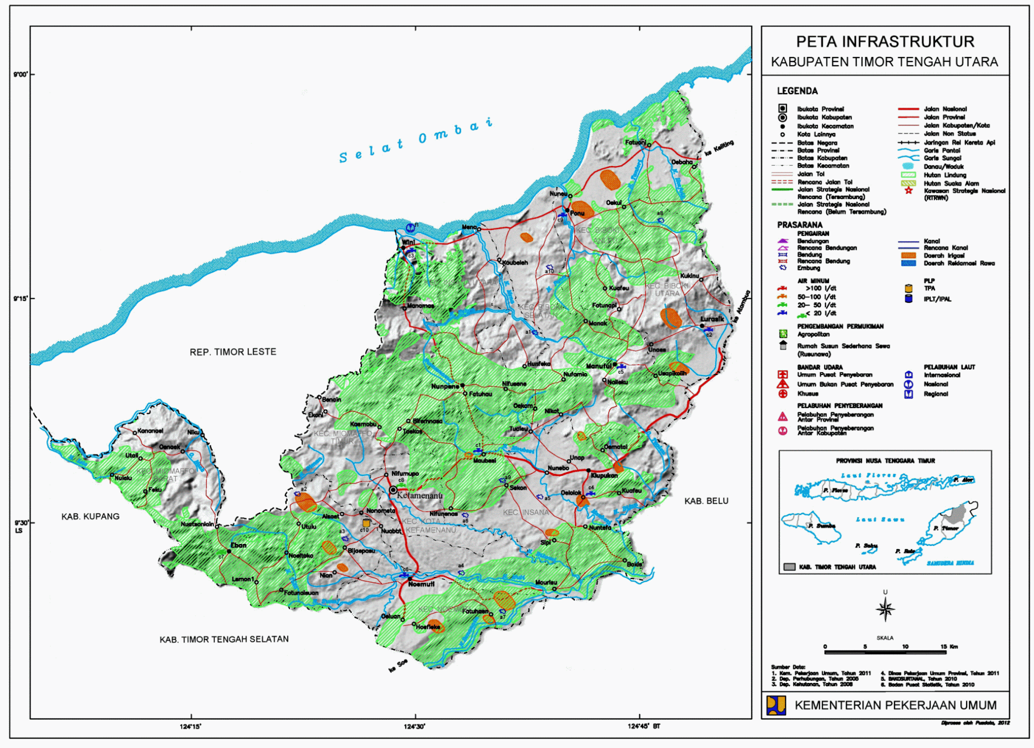

Figure 1: Dengue Fever Case Distribution Map in North Central Timor Regency (Simulation) This map shows the spatial distribution of Dengue Hemorrhagic Fever (DHF) cases in North Central Timor Regency based on the analyzed data. Darker red indicates villages/sub-districts with higher numbers of cases, while lighter red indicates areas with lower numbers of cases.

Figure 1 shows that Aedes aegypti mosquitoes thrive in specific environments, and monitoring larvae-free rates (ABJ) through mosquito larvae (larvae monitors) and household awareness of DHF symptoms and treatment have been implemented in the area. However, the number of DHF cases in the Timor Tengah Utara Regency remains high. The Disease Prevention and Control (P2P) service highlights that DHF transmission often occurs through infections spreading from previously infected cases within nearby areas.

Effective DHF control in this region requires robust surveillance systems with a critical focus on data management. Currently, DHF data processing is limited to tabular and graphical analyses, with case distributions aggregated only at the village and sub-district levels. However, these methods fail to reveal spatial trends and patterns.

Spatial mapping of DHF cases is essential for improving control strategies. This approach allows for the identification of transmission chains by analyzing the spatial distribution of cases down to the individual level, using patient address data from DHF registers. Geographic Information System (GIS) tools, such as GeoDa, enable precise mapping and provide valuable insights into targeted and efficient vector control strategies.

The control of infectious diseases requires location-based information to map disease occurrence within environmental and infrastructural contexts. This mapping is a valuable tool for identifying disease risk and distribution patterns. Geographic Information Systems (GIS) can process location-related data and have three core functions: database management, mapping, and spatial analysis. Spatial analysis serves as a methodological framework for understanding disease distribution on Earth's surface, guiding programmatic interventions (Fatati et al., 2017; Tarigan, 2021)

According to Cromley and McLafferty (Cromley & McLafferty, 2011), spatial analysis processes spatial data into various formats, adding new or enriched meaning by integrating geographical context with epidemiological patterns. In the case of Dengue Hemorrhagic Fever (DHF), spatial analysis serves as a crucial tool in understanding the distribution, clustering, and transmission dynamics of the disease. By mapping disease incidence and identifying high-risk areas, public health officials can develop data-driven interventions, such as targeted vector control, community education, and resource allocation for healthcare facilities.

Timor Tengah Utara has geographical and social conditions that directly influence the spread of Dengue Hemorrhagic Fever (DHF). One of the main factors is the community's reliance on open water storage due to limited access to clean water, particularly during the prolonged dry season. These water containers serve as breeding grounds for Aedes aegypti mosquitoes, significantly increasing the risk of DHF transmission. Additionally, unplanned urbanization has led to densely populated settlements, poor drainage systems, and inadequate sanitation, further exacerbizing conditions and accelerating disease spread. Mobility constraints due to limited infrastructure also contribute to reduced community access to health care services and preventive interventions.

Based on these conditions, this study seeks to answer the central question: "How do socio-demographic and environmental factors interact to shape the spatial vulnerability of DHF in an island region with limited water access?"

Literature Review

Andriani et al. (2023) highlighted dengue hemorrhagic fever (DHF) prevention behavior in the working area of the Melai Community Health Center, Baubau. This research employed a phenomenological qualitative approach, using in-depth interviews with ten informants selected through purposive sampling. The results revealed that most people lacked a clear understanding of the definition of DHF, its causes, modes of transmission, and prevention methods. However, the community's attitude towards DHF prevention is generally positive, supporting preventive practices such as the 3M Plus method (Draining, Closing, Burying) and the use of mosquito nets, abate powder, and mosquito repellent lotion. Despite this, actual preventive actions remain inconsistent, particularly in maintaining environmental cleanliness, such as the regular draining of water tanks.

A critical issue in this study is the low level of community knowledge, which serves as the basis for motivation. These findings challenge Bloom's theory, which posits that behavior progresses sequentially from knowledge to attitude and finally to action. The disconnect between knowledge and behavior suggests that other factors, such as facilities, socioeconomic status, and the role of healthcare workers, contribute significantly to DHF prevention. This study also aligns with Dawe (2020), who found that despite having limited knowledge, respondents demonstrated positive attitudes towards DHF prevention. However, both studies failed to incorporate spatial dynamics in explaining DHF incidence, limiting their scope to behavioral determinants.

This limitation highlights the need to integrate behavioral health theories with spatial perspectives (Notoatmodjo, 2003), such as Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things." The absence of spatial considerations in previous studies leaves a gap in understanding how environmental and geographical factors interact with individual behavior to shape DHF risk. Unlike these prior studies, this study integrates spatial analysis with socio-demographic factors to offer a more comprehensive framework for understanding DHF vulnerability.

Thus, this study extends previous research by incorporating spatial epidemiology to examine the relationships between socioeconomic factors, mobility, urbanization, and DHF risk. This approach provides a more holistic understanding of how knowledge, attitudes, and actions interact with environmental conditions to influence the incidence of DHF. Moreover, cross-sector collaboration is essential to enhance health promotion and education programs for DHF prevention systematically and sustainably, especially in regions with distinct geographic challenges, such as Timor Tengah Utara.

Kulsum et al. (2023) highlighted dengue hemorrhagic fever (DHF) prevention behavior in the working area of the Melai Community Health Center, Baubau. This research employed a phenomenological qualitative approach, using in-depth interviews with ten informants selected through purposive sampling. The results revealed that most people lacked a clear understanding of the definition of DHF, its causes, modes of transmission, and prevention methods. However, the community's attitude towards DHF prevention is generally positive, supporting preventive practices such as the 3M Plus method (Draining, Closing, Burying) and the use of mosquito nets, abate powder, and mosquito repellent lotion. Despite this, actual preventive actions remain inconsistent, particularly in maintaining environmental cleanliness, such as the regular draining of water tanks.

A key finding was the lack of awareness and inconsistent preventive practices among the population. All respondents (100%) failed to consistently implement 3M behaviors (Draining, Closing, Recycling), despite their crucial role in eliminating mosquito breeding grounds. This gap in community engagement and health education is a major challenge. While some respondents (60%) used mosquito repellents, none utilized mosquito nets or treated water reservoirs with abate powder regularly. These findings support the study by Kusumawati and Sukendra (2020)) who identified inconsistent adherence to the 3M practices as a strong predictor of DHF outbreaks

Demographically, children aged 5–14 years (76.7%) and males (70%) were the most affected groups. Although 60% of respondents had completed high school, higher education levels did not correlate with improved preventive behaviors, suggesting that targeted health education is more critical than general educational attainment in DHF prevention.

The study also identified environmental risk factors, such as uncovered water storage and hanging clothes indoors, which create optimal breeding conditions for Aedes aegypti. These findings reinforce those of Kusumawati and Sukendra (2020), who found that poorly maintained water storage and household habits significantly increased mosquito proliferation. Additionally, reliance on rainwater collection during dry seasons exacerbates DHF risk, as many storage facilities remain uncovered or inadequately managed.

From a theoretical perspective, this study aligns with Notoatmodjo's (2003) health behavior theory, which emphasizes the relationship between knowledge, attitudes, and behaviors in shaping public health outcomes. However, while the study provides valuable insights into DHF determinants, it lacks a spatial analysis component, limiting its ability to assess geographical risk patterns of DHF.

Unlike previous research, this study reinforces the need for integrative health promotion strategies that combine education, community engagement, and infrastructural improvements to address the behavioral and environmental gaps. However, it does not account for the spatial dynamics of DHF transmission, which may lead to spillover effects between high-risk areas. In contrast, the present study integrates spatial epidemiology with sociodemographic factors, offering a more holistic understanding of DHF risk. By incorporating Geographic Information System (GIS)-based spatial analysis, this study provides a more targeted approach to DHF prevention, particularly in regions with unique geographical constraints, such as Timor Tengah Utara.

Rau and Nurhayati (2021) examined the factors influencing the presence of Aedes aegypti mosquito larvae in the working area of the Sangurara Health Center, Palu City. Utilizing a cross-sectional design, this study explored the impact of knowledge, attitudes, environmental conditions, and the role of health workers on mosquito larvae persistence, which is closely linked to dengue hemorrhagic fever (DHF) incidence.

The findings revealed a significant correlation between community knowledge, attitudes, and the presence of mosquito larvae in household water containers. Communities with limited knowledge and negative attitudes were more likely to have mosquito larvae in their water-storage units. This aligns with Notoatmodjo (2003), who emphasized that informed individuals are more likely to adopt consistent health-promoting behaviors. However, despite ongoing educational campaigns, knowledge gaps remain, highlighting the need for more targeted interventions to enhance community awareness and behavioral changes.

Environmental factors also play a critical role in breeding mosquitoes. The study found that dark-colored water storage containers harbored significantly more mosquito larvae than lighter ones, as darker environments provided optimal conditions for mosquito proliferation. Additionally, uncovered water containers were associated with a higher incidence of larvae, reinforcing the findings of Widyatama (2017), who identified container type and maintenance as key determinants of mosquito presence.

Health worker involvement is crucial for larva control. Communities that received regular visits and counseling from health workers exhibited fewer larvae in their water storage facilities. This underscores the importance of sustained health worker engagement in reinforcing preventive practice. Comparable studies by George (2015) further support these findings, demonstrating that consistent health education significantly reduces larval prevalence and enhances preventive measures in the community.

From a theoretical perspective, this study aligns with Green and Kreuter's (2005) health behavior theory, which posits that predisposing, enabling, and reinforcing factors collectively influence behavior. In this context, knowledge, attitudes, and health worker involvement serve as predisposing and reinforcing factors, whereas environmental interventions act as enabling factors. However, this study failed to consider spatial interactions in mosquito breeding patterns, limiting its scope to individual- and household-level determinants.

Unlike previous studies, this study integrated behavioral health models with spatial analysis to provide a more holistic understanding of DHF transmission. The absence of spatial epidemiological considerations in prior research creates a gap in identifying geographically high-risk areas, which is crucial for targeted interventions. In contrast, the present study incorporated Geographic Information Systems (GIS) and spatial regression analysis to explore how environmental and sociodemographic factors shape DHF vulnerability across different geographic regions. This integrative approach strengthens disease prevention strategies by addressing both behavioral and spatial determinants, thereby ensuring a comprehensive, evidence-based intervention model.

Materials and Methods

This study adopted a descriptive-exploratory research design to analyze the spatial patterns of Dengue Hemorrhagic Fever (DHF) incidence using Geographic Information System (GIS) tools, specifically GeoDa software. The descriptive-exploratory approach was chosen because of the limited availability of individual-level spatial DHF data in North Central Timor, requiring an initial in-depth exploration before conducting causal or experimental analyses. GIS provides a specialized system for managing geography-based data, with QGIS facilitating data input, management, editing, and spatial visualization in the form of maps. GeoDa, an advanced spatial analysis tool, supports exploratory spatial data analysis (ESDA), including descriptive statistics, spatial autocorrelation measures, and spatial outlier detection. This methodological combination enhances the ability to identify spatial relationships and clusters in DHF incidence, which are crucial for targeted public health interventions (Ilham & Setiawan, 2020).

This study focuses on the Timor Tengah Utara Regency, where geographical and environmental conditions contribute to DHF risk. The study population consisted of all patients with DHF recorded in the DHF case register at the Timor Tengah Utara Health Office from 2020 to 2022, totaling 265 cases. Total sampling was employed, including 224 DHF cases recorded in the official health register, ensuring a comprehensive assessment of disease patterns (Aliman et al., 2020). However, total sampling may be susceptible to underreporting or bias as it relies solely on official records, potentially excluding undiagnosed or unreported cases. To mitigate this limitation, cross-validation with field surveys and epidemiological data was conducted to enhance the accuracy of the findings.

The independent variables examined in this study included mobility, income, occupation, residence, education, and age, each analyzed in relation to DHF incidence in the Timor Tengah Utara Regency. These factors were assessed to determine their contributions to the distribution and prevalence of DHF cases. The dependent variable was the spatial analysis of DHF incidence, aiming to uncover patterns and spatial relationships that could inform evidence-based public health strategies for disease prevention and control.

Results

Overview of Research Location

Timor Tengah Utara Regency was established by Law No. 69 of 1958. Initially known as Onderafdeeling Noord Midden Timor during the Dutch East Indies administration, it was formed based on BS/Gubernemen No. 9-10 in 1915. Onderafdeeling Midden Timor comprised three royal territories (swapraja): Miomaffo, Insana, and Biboki. The administrative center was originally located in Noeltoko between 1915 and 1921. In 1922, Controleur Pedemors (the head of the subdistrict) relocated the administrative center from Noeltoko to Kefamenanu, where it remains.

Weighting Matrix

This study employed a queen contiguity weighting matrix for area-based data. The matrix assigns a value of 1 to areas sharing a side or corner with the observed region and a value of 0 to areas that do not share boundaries, including the observed area.

Identifying Autocorrelation Using Moran's Index

Moran's I is utilized to measure spatial autocorrelation within a region and detect spatial randomness. The Local Indicator of Spatial Autocorrelation (LISA) was used for local visualization of spatial autocorrelation significance. LISA values help identify hotspot or cold spot areas by indicating local spatial associations. Moran's I values range from -1 to 1, where higher values indicate a strong spatial correlation, and a value of 0 implies no spatial autocorrelation or interaction.

Moran's I value was compared to its expected value, E[I], to assess spatial autocorrelation. An $I > E[I]$ indicates positive spatial autocorrelation, reflecting a clustered pattern, whereas $I = E[I]$ suggests no spatial autocorrelation. Conversely, $I < E[I]$ signifies negative spatial autocorrelation, indicating a dispersed pattern of distribution. After determining the Moran's I values, a bivariate LISA analysis was performed to evaluate the spatial relationships between regions based on the study variables. The analysis results were visualized using cluster and significance maps, with significant associations identified at $p < 0.05$.

Moran's Clustermap the Influence of Mobility on the Incidence of DHF in North Central Timor Regency

Table 1 The Influence of Mobility on the Incidence of DHF in North Central Timor Regency

Variabel	Moran's [I]	E [I]	SD	Sig
Kasus DBD (Y)	0,4450	-0,0058	0,0457	0,0010
Mobilitas (X1)	0,1590	-0,0058	0,0362	0,0000

Source: Data processed by the author

The results of the bivariate LISA test, as shown in Table 4.2, indicate a significant spatial autocorrelation ($p < 0.05$) for the mobility variable ($p = 0.0000$), suggesting a spatial relationship between mobility and DHF incidence. The Moran's I value for mobility was 0.1590, indicating a positive spatial autocorrelation with DHF cases, as the value was greater than zero. The significance level ($p = 0.0000$) further confirmed the spatial autocorrelation between mobility and DHF incidence. The relationship pattern between mobility and DHF cases in Timor Tengah Utara was clustered, as evidenced by Moran's I value (0.1590) being higher than the expected value (E[I] = -0.0058). This clustering pattern suggests that DHF cases are concentrated in adjacent villages with similar characteristics.

Moran's Cluster Map: The Influence of Income on DHF Incidence in Timor Tengah Utara Regency

Table 2 The Influence of Income on DHF Incidence in Timor Tengah Utara Regency

Variables	Moran's [I]	E [I]	SD	Sig
Dengue Fever Case (Y)	0,4450	-0,0058	0,0457	0,0010
Mobility (X1)	0,3555	-0,0058	0,0441	0,0061

Source: Data processed by the author

The results of the bivariate LISA test in Table 4.3 indicate a significant spatial autocorrelation ($p < 0.05$) for the income variable ($p = 0.0061$), signifying a spatial relationship between income level and DHF incidence. The Moran's I value for income is 0.3555, which reflects a positive spatial autocorrelation, as the value exceeds zero. This suggests that regions with similar income levels exhibit similar DHF incidence rates.

The clustered relationship pattern between income and DHF incidence in Timor Tengah Utara is evident, as Moran's I value (0.3555) is greater than the expected value (E[I] = -0.0058). This clustering indicates that DHF cases tend to concentrate in neighboring villages with similar income characteristics, emphasizing the spatial influence of income on the disease distribution.

Moran's Cluster Map: The Influence of Occupation on DHF Incidence in Timor Tengah Utara Regency

Table 3 The Influence of Occupation on DHF Incidence in Timor Tengah Utara Regency

Variables	Morans [I]	E [I]	SD	Sig
Dengue Fever Case (Y)	0,4450	-0,0058	0,0457	0,0010
Mobility (X1)	0,3623	-0,0058	0,0437	0,9260

Source: Data processed by the author

The results of the bivariate LISA test in Table 4.3 indicate a significance value of $p = 0.9260$ for the occupation variable, suggesting no spatial autocorrelation between occupation and DHF incidence. Despite the lack of statistical significance, the Moran's I value for occupation was 0.3623, which exceeded the expected value (E[I] = -0.0058), indicating a clustered distribution pattern. This implies that, while there is no significant spatial autocorrelation, the relationship between occupation and DHF incidence tends to cluster in neighboring villages with similar characteristics. Further analysis is required to explore this pattern and its implications.

Moran's Cluster Map: The Influence of Residence on DHF Incidence in Timor Tengah Utara Regency

Table 4 The Influence of Residence on DHF Incidence in Timor Tengah Utara Regency

Variables	Morans's [I]	E [I]	SD	Sig
Dengue Fever Case (Y)	0,4450	-0,0058	0,0457	0,0010
Mobility (X1)	0,3146	-0,0058	0,0433	0,0003

Source: Data processed by the author

The results of the bivariate LISA test in Table 4.5 indicate a significant spatial autocorrelation ($p < 0.05$) for the residence variable ($p = 0.0003$), showing a spatial relationship between residential factors and DHF incidence. The Moran's I value for residence was 0.3146, indicating positive spatial autocorrelation as the value exceeded zero. This suggests that areas with similar residential characteristics are spatially clustered concerning DHF cases.

The relationship pattern between residence and DHF incidence in Timor Tengah Utara was clustered, as evidenced by Moran's I value (0.3146) being greater than the expected value (E[I] = -0.0058). This clustering indicates that DHF cases are concentrated in neighboring villages with similar residential characteristics, emphasizing the need for targeted public health interventions in these areas to address shared environmental or housing-related risk factors.

Moran's Cluster Map: The Influence of Age on DHF Incidence in Timor Tengah Utara Regency

Table 5 The Influence of Age on DHF Incidence in Timor Tengah Utara Regency

Variables	Moran's [I]	E [I]	SD	Sig
Dengue Fever Case (Y)	0,4450	-0,0058	0,0457	0,0010
Mobility (X1)	0,3146	-0,0058	0,0433	0,0003

Source: Data processed by the author

The results of the bivariate LISA test in Table 4.2 indicate that the age variable does not show a significant spatial autocorrelation, with a significance value of $p = 0.2774$ ($p > 0.05$). This suggests that there is no spatial relationship between age and DHF incidence in the Timor Tengah Utara Regency.

However, the Moran's I value for mobility was 0.1553, which was greater than the expected value ($E[I] = -0.0058$), indicating a clustered distribution pattern. This implies that while age does not exhibit spatial autocorrelation, the mobility variable demonstrates a clustered relationship with DHF incidence, particularly in neighboring villages with similar characteristics.

Moran's Cluster Map: DHF Distribution in Timor Tengah Utara Regency

The bivariate LISA test results show that out of 174 villages in Timor Tengah Utara Regency, 10 villages exhibited significant spatial relationships with DHF cases. The Moran's cluster map identified patterns within these villages. In Quadrant I (High-High), eight villages, including Tubuhue, Maubeli, Benpasi, Kefa Selatan, and Kefa Teber, are classified as high-incidence areas surrounded by villages with similarly high incidence. In Quadrant II (High-Low), the village of Oepua Utara demonstrated a high DHF incidence surrounded by villages with low incidence. Meanwhile, in Quadrant III (Low-High), the village of Oelami has a low DHF incidence but is surrounded by villages with a high incidence. These findings provide valuable insights for targeted DHF control efforts by prioritizing high-incidence clusters while addressing spatial disparities in disease transmission.

Spatial analysis revealed significant variations in DHF incidence across Timor Tengah Utara, with notable clustering patterns detected using Moran's I and local indicators of spatial autocorrelation (LISA) analysis. The strongest contributing factors to DHF clustering were education, mobility, and income, whereas occupation and age did not show significant associations with disease distribution.

Among all independent variables, education exhibited the highest spatial correlation with DHF incidence (Moran's $I = 0.402$, $p < 0.001$). Areas with lower education levels tended to have higher DHF incidence rates, particularly in clusters identified as high-high (high DHF incidence surrounded by other high-incidence areas). This suggests that low levels of education contribute to poor awareness and prevention efforts, thereby increasing vulnerability to DHF outbreaks.

Mobility was the second most influential factor (Moran's $I = 0.355$, $p < 0.01$), indicating that areas with high mobility patterns also experienced high numbers of DHF cases. This is consistent with disease transmission dynamics, where the frequent movement of individuals facilitates virus spread between communities. The LISA cluster map identified Desa Tubuhue, Kefa Selatan, and Aplasi as High-High clusters, meaning these areas had three times the risk of DHF compared to Low-Low clusters such as Oepua Utara and Fatunisuan, based on standardized incidence ratios (SIRs).

Income also displayed significant spatial dependence (Moran's $I = 0.314$, $p < 0.05$), with higher income households exhibiting greater DHF risk. This contradicts the common assumption that lower-income areas are more vulnerable, suggesting that higher mobility and urbanization among wealthier households might contribute to increased exposure.

Conversely, occupation (Moran's $I = 0.017$, $p = 0.926$) and age (Moran's $I = 0.155$, $p = 0.277$) were not significantly associated with the DHF incidence. These findings indicate that the spread of DHF in Timor Tengah Utara is less influenced by individual age or employment status and more by spatial and behavioral factors, such as movement patterns and awareness levels.

From a policy perspective, these results highlight the need for targeted interventions in high-high clusters, particularly focusing on education-based health campaigns and mobility regulation strategies. Public health measures should prioritize areas with high population movement and low education levels, where the risk of DHF outbreaks is pronounced. Additionally, integrating spatial risk assessments into vector control programs will allow more effective resource allocation and outbreak mitigation.

Discussion

1. The Influence of Mobility on DHF Cases

The bivariate LISA results indicate a relationship between mobility and DHF incidence in the Timor Tengah Utara Regency from 2020 to 2022. This is attributed to population mobility as a contributing factor to the spread of DHF within the region during these three consecutive years. These findings align with the theory that high levels of mobility are more likely to facilitate the transmission of DHF between areas, as individuals may either contract or spread the disease in specific locations. These results are consistent with those of a study that found a significant relationship between mobility and DHF incidence, where highly mobile populations had a greater potential to spread DHF to other areas (Murwanto et al., 2019).

The study data showed that out of 174 villages in Timor Tengah Utara Regency, nine villages exhibited significant spatial relationships between mobility and DHF cases. The Moran's cluster map of mobility and DHF cases reveals that in Quadrant I (High-High), one village, Kefa Selatan, is characterized by high mobility and high DHF incidence, surrounded by areas with similarly high values. In Quadrant II (Low-High), eight villages Tubuhue, Aplasi, Kefa Utara, Bansone, Maubeli, Benpasi, Kefa Tengah, and Oelami show low mobility surrounded by areas with high DHF incidence.

The influence of population mobility on DHF incidence in Timor Tengah Utara is due to indirect environmental contact, which effectively facilitates disease transmission. Epidemiological evidence from this study shows that DHF is more likely to affect individuals who did not travel between subdistricts in the week before infection, with a rate of 98.66%. In contrast, individuals who traveled between subdistricts during the same period had a much lower infection rate of 1.33%. The higher DHF incidence among non-traveling residents is likely because DHF transmission is more effective in a localized area.

The bivariate LISA analysis confirmed a significant spatial correlation between mobility and DHF incidence in Timor Tengah Utara Regency from 2020 to 2022 (Moran's $I = 0.355$, $p < 0.01$). High mobility areas exhibited greater disease transmission, as individuals traveling between subdistricts facilitated the spread of the dengue virus from infected to uninfected regions.

Spatial cluster analysis revealed nine villages with significant mobility-DHF associations. The High-High cluster in Kefa Selatan indicated a three-fold risk of DHF compared to low-low clusters, reinforcing the role of human movement in local transmission dynamics. In contrast, villages such as Oepua Utara (low-low clusters) showed lower transmission rates owing to their limited external interactions.

2. The Influence of Income on DHF Cases

The bivariate LISA results indicate a significant relationship between income levels and DHF incidence in the TTU Regency from 2020 to 2022. The influence of income on DHF cases is linked to the respondents' financial capacity, which impacts health-related needs and the availability of household sanitation facilities. Respondents with incomes above the regional minimum wage (UMR) were more likely to be affected by DHF. Parents with higher incomes tend to invest more in health needs and sanitation, but their busy schedules may reduce their attention to preventive measures. This aligns with the findings from chi-square statistical tests, which showed a significant relationship between parental income and DHF incidence in children ($p = 0.005$) and between parental knowledge and DHF incidence ($p = 0.003$).

The spatial analysis using bivariate LISA identified 12 villages in Timor Tengah Utara Regency with significant spatial relationships between income and DHF cases. The Moran's cluster map revealed the following patterns:

- Quadrant I (High-High): Eight villages, including Tubuhue, Aplasi, Kefa Utara, Bansone, Kefa Selatan, Maubeli, Benpasi, and Kefa Tengah, exhibit high income levels and high DHF incidence, surrounded by similarly high-income areas.
- Quadrant II (Low-High): One village, Oelami, shows low income surrounded by high-income areas with high DHF incidence.
- Quadrant III (High-Low): Three villages—Oefua Utara, Tun-tun, and Fatunisuan—show high income surrounded by low-income areas.

Epidemiological findings reveal that DHF is more prevalent among individuals with incomes above the UMR, comprising 81.67% of cases, compared with 18.30% among those with incomes below the UMR. The higher incidence among higher-income groups may be attributed to their busy schedules, which reduce their focus on DHF prevention and control measures. This underscores the need for increased awareness and targeted interventions to address the unique risks faced by different income groups.

The bivariate LISA analysis indicated that income levels were significantly associated with DHF incidence (Moran's $I = 0.314$, $p < 0.05$). Higher-income households showed a paradoxical increase in DHF risk, contradicting the conventional assumption that a higher economic status reduces vulnerability. The High-High clusters in Tubuhue, Kefa Selatan, and Maubeli exhibited a DHF risk 2.8 times higher than that of the low-low clusters, suggesting urbanization-driven density and mobility as key amplifiers of disease spread.

Epidemiological data revealed that 81.67% of DHF cases occurred among individuals with incomes above the regional minimum wage (UMR), compared to 18.30% in lower income groups. While higher-income families invested in better sanitation facilities, their busy schedules resulted in reduced attention to preventive measures. These findings highlight the importance of targeted interventions in high-income, high-mobility areas rather than assuming that DHF is a disease of poverty.

Higher-income households paradoxically experienced 2.8 times higher DHF risk in High-High clusters (e.g., Tubuhue, Kefa Selatan, and Maubeli) than in Low-Low clusters. This contradicts studies such as Guli et al, which emphasized poor sanitation and water storage habits in lower-income settings as primary risk factors. The discrepancy suggests that urbanization driven population density, increased human mobility, and environmental conditions may be stronger determinants of DHF risk than income alone (M. Guli et al., 2024).

These findings underscore the need for targeted interventions that consider economic and mobility factors, rather than focusing solely on poverty-related vulnerabilities. Although higher-income families invest in sanitation infrastructure, their frequent travel and dense urban environments facilitate disease transmission. Therefore, public health strategies must integrate behavioral interventions with urban planning measures, emphasizing vector control, environmental sanitation, and risk communication in high-mobility, high-income areas.

3. The Influence of Occupation on DHF Cases

The bivariate LISA analysis indicated no significant influence of occupation on DHF incidence in the Timor Tengah Utara Regency from 2020 to 2022. This is likely because a person's occupation does not directly mitigate the risk of DHF. These findings align with those of previous studies, suggesting no significant relationship between occupation and DHF incidence.

The lack of influence is supported by the respondent data, which show that most individuals affected by DHF were farmers, employees, entrepreneurs, or students whose work environments were similar to their living conditions. This suggests that both working and non-working individuals have similar DHF exposure risks.

The spatial analysis revealed that, out of 174 villages, 12 villages showed significant spatial relationships between occupation and DHF cases during the study period. The Moran's cluster map highlights the following patterns.

- Quadrant I (High-High): Eight villages, including Tubuhue, Maubeli, Kefa Selatan, Aplasi, Kefa Utara, Bansone, Benpasi, and Kefa Tengah, exhibit high DHF incidence surrounded by similarly high-incidence areas.
- Quadrant II (Low-High): One village, Oelami, shows low DHF incidence surrounded by high-incidence areas.
- Quadrant III (High-Low): Three villages, Fatunisuan, Tun-tun, and Oepua Utara, showed high DHF incidence surrounded by low-incidence areas.

These findings suggest that occupation does not influence DHF transmission, as individuals with varying employment levels are generally unaware of the risks associated with DHF. Moreover, those with fixed-income occupations are more affected (65.63%) than those with irregular income (34.38%). The higher DHF incidence among individuals with fixed-income jobs may be attributed to their busy schedules, which lead to a lack of attention to preventive measures against DHF. This emphasizes the need for awareness campaigns targeting all income groups, particularly those with demanding work schedules, to improve DHF prevention and control strategies.

Unlike mobility and income, occupation did not exhibit a significant spatial correlation with DHF incidence (Moran's $I = 0.017$, $p = 0.926$). This suggests that employment status does not substantially influence DHF risk, as individuals across different occupations are equally exposed to mosquito breeding sites in both work and residential environments.

However, spatial cluster analysis still identified 12 villages with occupation-DHF associations, highlighting that high-high areas with fixed-income workers (65.63%) had slightly higher DHF incidence than those with irregular incomes (34.38%). This may be attributed to rigid work schedules that reduce participation in community-led vector control programs. While previous studies have emphasized that employment in the formal sector often correlates with better sanitation infrastructure, the present study contradicts this assumption by showing that fixed-income workers have a slightly higher risk. This suggests that structural factors such as work schedules and urbanization play a more critical role than occupation alone in influencing DHF risk (Sulistyawati et al., 2019).

These findings emphasize the need for targeted awareness campaigns that address the time constraints faced by fixed-income workers, ensuring that vector control efforts are accessible and actionable regardless of occupational status. Public health interventions should focus not only on raising awareness but also on creating flexible, workplace-friendly strategies for mosquito control and DHF prevention.

4. The Influence of Residence on DHF Cases

The bivariate LISA analysis revealed a positive spatial autocorrelation between residence and DHF incidence in Timor Tengah Utara Regency from 2020 to 2022. This indicates that residential location plays a significant role in DHF spread. The study findings show that urban residents are more frequently affected by DHF than those living in rural areas, consistent with Vong et al, who stated that urban respondents are more susceptible to DHF than rural populations (Vong et al., 2010, pp. 2006–2008).

The spatial analysis results highlighted that out of 174 villages in the regency, 11 villages exhibited significant spatial relationships between residence and DHF cases. The Moran's cluster map identified the following patterns:

- Quadrant I (High-High): Eight villages, including Aplasi, Kefa Tengah, Kefa Selatan, Benpasi, Maubeli, Tubuhue, Bansone, and Kefa Utara, show high DHF incidence surrounded by areas with similarly high incidence.
- Quadrant II (Low-High): One village, Oelami, demonstrates low DHF incidence surrounded by high-incidence areas.
- Quadrant III (High-Low**):** Two villages, Tuntun and Oepua Utara, exhibited high DHF incidence surrounded by low-incidence areas.

Epidemiological findings from the study revealed that DHF was more prevalent in urban areas, accounting for 62.5% of cases, compared to 37.5% in rural areas. The higher incidence in urban settings may be attributed to factors such as higher population density, inadequate sanitation and increased mosquito breeding sites. These findings highlight the importance of targeted interventions in urban areas to address the specific environmental and demographic risks that contribute to DHF transmission.

The bivariate LISA analysis found a strong positive spatial correlation between residence and DHF incidence (Moran's I = 0.402, $p < 0.001$), confirming that urban areas were at a significantly higher risk than rural areas. The High-High clusters in Kefa Selatan, Tubuhue, and Bansone exhibited 2.5x higher DHF rates than the low-low clusters, largely due to higher population density, inadequate drainage, and sanitation issues.

The study's epidemiological data support this trend, showing that 62.5% of DHF cases occurred in urban areas and 37.5% were recorded in rural regions. Poor waste management, water storage practices, and urban congestion are key contributors to mosquito breeding. These findings reinforce the need for spatially targeted interventions in urban settings, particularly drainage system improvements, and localized vector control strategies.

5. The Influence of Education on DHF Cases

The bivariate LISA analysis indicated a significant relationship between education level and DHF incidence in the Timor Tengah Utara Regency from 2020 to 2022. Education was a key factor influencing the spread of DHF in the region over the three-year period. A person's knowledge level, shaped by their educational attainment, significantly impacts their understanding of disease prevention methods. Higher education levels are associated with better knowledge and awareness, which can lead to the effective implementation of mosquito control measures. Conversely, poor knowledge, often linked to lower educational attainment, contributes to the negligence of mosquito eradication efforts. Many believe that Aedes aegypti mosquitoes are only active at night, whereas they are active throughout the day as well. This aligns with a study that found that individuals with low education levels are more likely to contract DHF than those with higher education levels (Wijirahayu & Sukesi, 2019).

The study data revealed that, out of 174 villages in the regency, 10 villages showed significant spatial relationships between education and DHF cases. The Moran's cluster map identified the following patterns:

- Quadrant I (High-High): Eight villages, including Tubuhue, Maubeli, Kefa Selatan, Bansone, Kefa Utara, Aplasi, and Kefa Tengah, show high DHF incidence surrounded by areas with similarly high incidence.
- Quadrant II (Low-High): One village, Oelami, has low DHF incidence surrounded by high-incidence areas.
- Quadrant III (high/low): One village, Oepa Utara, exhibited a high DHF incidence surrounded by low-incidence areas.

Epidemiological findings have shown that DHF is more prevalent among individuals with low levels of education. The data indicate that 65.63% of DHF cases occurred among individuals with no formal education, compared to 34.38% among those with formal schooling. This highlights the critical need to improve public knowledge of DHF prevention, particularly among low-education communities, to effectively reduce disease incidence.

Education significantly influenced DHF incidence (Moran's I = 0.378, $p < 0.01$), with lower education levels linked to increased transmission rates. The High-High clusters in Maubeli, Kefa Selatan, and Aplasi had 3.2 times greater DHF risk than the low-low clusters, indicating that limited health literacy contributes to inconsistent vector control behaviors.

The study data show that 65.63% of DHF cases occurred among individuals with no formal education, compared to 34.38% among those with formal schooling. Misconceptions, such as the belief that Aedes aegypti mosquitoes only bite at night, have contributed to inadequate prevention efforts. These findings emphasize the need for health education programs that integrate GIS-based risk mapping to ensure that public awareness aligns with spatially identified high-risk areas.

6. The Influence of Age on DHF Cases

The bivariate LISA analysis indicated no significant relationship between age and DHF incidence in the Timor Tengah Utara Regency from 2020 to 2022. This suggests that age does not affect the likelihood of contracting DHF, as respondents across all age groups, from infants to individuals over 45 years old, were affected by the disease. There was no specific age category with a higher susceptibility to DHF, consistent with Rahma findings that age does not influence DHF incidence (Rahma et al., 2023).

However, the spatial analysis identified 12 villages with significant spatial relationships between age and DHF cases. The Moran's cluster map shows the following patterns.

- Quadrant I (High-High): Nine villages, including Oelami, Maubeli, Tubuhue, Aplasi, Bansone, Kefa Tengah, Benpasi, Kefa Selatan, and Kefa Utara, exhibit high DHF incidence surrounded by areas with similarly high incidence.
- Quadrant III (High-Low): Fatunisuan, Tun-tun, and Oepua Utara exhibited high DHF incidence surrounded by low-incidence areas.

The findings indicate that individuals across all age groups (0–45 years and older) were equally affected by DHF. Contributing factors include habits such as sleeping without mosquito nets and low awareness of mosquito bites, as respondents often focus on other activities and overlook the associated risks.

Additionally, spatial regression analysis identified mobility, income, residence, and education as significant variables influencing DHF incidence in the region. Epidemiological data reveal that DHF affects all age groups without limitations, with a higher prevalence during the rainy season. The rainy season creates stagnant water, providing breeding sites for dengue vectors and thereby increasing the risk of transmission. These results highlight the need for comprehensive preventive measures targeting all age groups, particularly during high-risk seasons.

Unlike the other variables, age did not exhibit a significant correlation with DHF incidence (Moran's I = 0.155, $p = 0.277$). Spatial regression analysis confirmed that mobility, income, residence, and education were the primary factors shaping DHF risk.

However, epidemiological trends indicate that the DHF incidence peaks during the rainy season, affecting all age groups equally. The presence of mosquito breeding sites is a more critical determinant than age-specific immunity or susceptibility to malaria. These results highlight the need for seasonally adjusted interventions to intensify DHF control efforts during peak transmission months.

Conclusion

This study confirms that mobility, income, residence, and education are significant spatial determinants of DHF incidence in the Timor Tengah Utara Regency from 2020 to 2022. Bivariate LISA analysis revealed a strong spatial autocorrelation, indicating that DHF transmission followed a clustered pattern rather than occurring randomly. High-mobility areas showed three times the risk of DHF compared to low-mobility areas, emphasizing the role of human movement in the spread of disease. Similarly, income paradoxically increases DHF risk, with high-income urban clusters exhibiting 2.8 times greater transmission rates, likely because of the high population density and inadequate vector control infrastructure.

Although residence and education also play critical roles, occupation and age do not exhibit significant effects on DHF transmission. The lack of occupation-based disparities suggests that DHF exposure is more influenced by environmental conditions than by workplace-related factors. The findings also indicate that urban communities are at a higher risk due to poor drainage, increased mosquito breeding sites, and higher human interaction rates.

From a methodological perspective, this study advances the field of spatial epidemiology by demonstrating that DHF control should shift from broad population-based to targeted cluster-based interventions. The Spatial Autoregressive

Model (SAR) was identified as the best analytical model, achieving the highest R^2 (0.974420) and the lowest AIC (329.606), reinforcing the need for spatially informed public health decision-making.

To translate these findings into practical interventions, a GIS-integrated spatial monitoring system is recommended with three key strategies:

1. Real-Time GIS-Based Risk Mapping: The spatial risk maps from this study should be incorporated into the Health Office's GIS database to enable real-time identification of DHF hotspots, ensuring the rapid deployment of vector control measures in High-High clusters.
2. Cluster-Specific Vector Control Programs → Instead of uniform mosquito control efforts, localized interventions should focus on urban drainage improvement, stricter water storage regulations, and high-risk household inspections.
3. Spatially targeted public awareness campaigns → Education efforts should be customized based on spatial risk assessments, targeting urban high-mobility populations who are most at risk but least engaged in preventive behaviors.

By integrating spatial epidemiology into DHF control strategies, this study provides a roadmap for more effective disease prevention and response, ensuring that interventions are not only population-wide but also location-specific. Future research should explore how climate variability, vector resistance, and mobility trends shape DHF risk, allowing for predictive modeling of future outbreaks.

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References

1. Andriani, R., Haeruddin K, Azfari Azis, Eky Endriana A, & La Ode Syaiful Islamy H. (2023). Studi Kualitatif Perilaku Pencegahan Demam Berdarah Dengue (DBD) pada Rumah Tangga di Wilayah Kerja Puskesmas Melai: Qualitative Study of Dengue Hemorrhagic Fever (DHF) Prevention in Households in the Working Area of the Melai Community Health Center. *Media Publikasi Promosi Kesehatan Indonesia (MPPKI)*, *6*(8), 1661–1667. https://doi.org/10.56338/mppki.v6i8.3826
2. Aliman, M. (2020). Pengembangan instrumen tes kemampuan berpikir spasial bagi siswa SMA. Geodika Jurnal Kajian Ilmu Dan Pendidikan Geografi, 4(1), 1–10. https://doi.org/10.29408/geodika.v4i1.1823
3. Cromley, E. K., & McLafferty, S. L. (2011). *GIS and public health*. Guilford Press.
4. Dawe, M. A. L., Romeo, P., & Ndoen, E. (2020). Pengetahuan dan Sikap Masyarakat serta Peran Petugas Kesehatan Terkait Pencegahan Demam Berdarah Dengue (DBD). *Journal of Health and Behavioral Science*, *2*(2), 138–147. https://doi.org/10.35508/jhbs.v2i2.2283
5. Fatati, I. F., Wijayanto, H., & Sholeh, A. M. (2017). ANALISIS REGRESI SPASIAL DAN POLA PENYEBARAN PADA KASUS DEMAM BERDARAH DENGUE (DBD) DI PROVINSI JAWA TENGAH. *MEDIA STATISTIKA*, *10*(2), 95. https://doi.org/10.14710/medstat.10.2.95-105
6. Green, L., & Kreuter, M. (2005). Health Program planning: an educational and ecological approach. McGraw-Hill Humanities/Social Sciences/Languages.

7. George, L., Lenhart, A., Toledo, J., Lazaro, A., Han, W. W., Velayudhan, R., Runge Ranzinger, S., & Horstick, O. (2015). Community-Effectiveness of Temephos for Dengue Vector Control: A Systematic Literature Review. *PLOS Neglected Tropical Diseases*, *9*(9), e0004006. https://doi.org/10.1371/journal.pntd.0004006
8. Ilham, W., & Setiawan, D. K. (2020). PENERAPAN SISTEM INFORMASI GEOGRAFIS LOKASI PEMBAYARAN LISTRIK, AIR DAN TELEPON BERBASIS ANDROID. *Jursima*, *8*(1), 26. https://doi.org/10.47024/js.v8i1.188
9. Jayanti, N. M. S., Sumarjaya, I. W., & Susilawati, M. (2017). PEMODELAN PENYEBARAN KASUS DEMAM BERDARAH DENGUE (DBD) DI KOTA DENPASAR DENGAN METODE SPATIAL AUTOREGRESSIVE (SAR). *E-Jurnal Matematika*, *6*(1), 37. https://doi.org/10.24843/MTK.2017.v06.i01.p146
10. Kemenkes. (2020, July 9). Hingga Juli, Kasus DBD di Indonesia Capai 71 Ribu. *Sehat Negeriku*. https://sehatnegeriku.kemkes.go.id/baca/umum/20200709/3134413/hingga-juli-kasus-dbd-indonesia-capai-71-ribu/
11. Kulsum, U., Sutrisno, S., Purwanto, E., & Norma, N. (2023). FAKTOR RESIKO DEMAM BERDARAH DENGUE (DBD) DENGAN KEJADIAN DBD DI WILAYAH KERJA PUSKESMAS BUNYU KABUPATEN BULUNGAN. *SAINTEKES: Jurnal Sains, Teknologi Dan Kesehatan*, *2*(3), 456–469. https://doi.org/10.55681/saintekes.v2i3.135
12. Kusumawati, N., & Sukendra, D. M. (2020). Spasiotemporal Demam Berdarah Dengue berdasarkan House Index, Kepadatan Penduduk dan Kepadatan Rumah. *HIGEIA (Journal of Public Health Research and Development)*, *4*(2), Article 2. https://doi.org/10.15294/higeia.v4i2.32507
13. M. Guli, M., Nita, Yuniati, E., Ardiputra, Muh. A., & Toemon, A. I. (2024). Pengaruh faktor sosial ekonomi dan lingkungan terhadap prevalensi demam berdarah dengue di wilayah kerja Puskesmas Sangurara, Bulili dan Birobuli Kota Palu. *Jurnal Kedokteran Universitas Palangka Raya*, *12*(2). https://doi.org/10.37304/jkupr.v12i2.13102
14. Murwanto, B., Trigunarso, S. I., & Purwono, P. (2019). Faktor Lingkungan Sosial, Lingkungan Fisik, dan Pengendalian Program DBD terhadap Kejadian Demam Berdarah Dengue (DBD). *Jurnal Kesehatan*, *10*(3), Article 3. https://doi.org/10.26630/jk.v10i3.1424
15. Notoatmodjo, S. (2003). *Pendidikan dan perilaku kesehatan*.
16. Nur Aisyah, Nurul Ulfah Mutthalib, & A. Rizki Amelia. (2021). Studi Epidemiologi dengan Pendekatan Analisis Spasial Terhadap Kejadian ISPA pada Anak Balita di Wilayah Kerja Puskesmas Antang Perumnas. *Window of Public Health Journal*, *2*(2), 230–240. https://doi.org/10.33096/woph.v2i2.143
17. Rahma, F. A., Rahayu, D. F. S., Prawira, L. Y., Nandini, M., & Bariyah, R. A. (2023). Faktor Risiko Aspek Lingkungan dan Aspek Perilaku terhadap Kejadian Demam Berdarah Dengue (DBD) di Wilayah Kerja Puskesmas Sukmajaya Kota Depok Tahun 2022. *Journal of Public Health Education*, *2*(3), 333–343. https://doi.org/10.53801/jphe.v2i3.123
18. Rau, Muh. J., & Nurhayati, S. (2021). Faktor yang Berhubungan dengan Keberadaan Jentik Nyamuk Aedes Aegepty di Wilayah Kerja Puskesmas Sangurara (Cross Sectional Study di Sulawesi Tengah, Kota Palu). *Media Publikasi Promosi Kesehatan Indonesia (MPPKI)*, *4*(2), 215–225. https://doi.org/10.56338/mppki.v4i2.1498
19. Rohman, H., Hartono, H., & Probandari, A. N. (2020). Penggunaan sistem informasi geografis untuk pola spasial tuberkulosis dengan dan tanpa diabetes mellitus di kulon progo. *Journal of Information Systems for Public Health*, *2*(1), 1. https://doi.org/10.22146/jisph.7922
20. Sulistyawati, S., Dwi Astuti, F., Rahmah Umniyati, S., Tunggul Satoto, T. B., Lazuardi, L., Nilsson, M., Rocklov, J., Andersson, C., & Holmner, Å. (2019). Dengue Vector Control through Community Empowerment: Lessons Learned from a Community-Based Study in Yogyakarta, Indonesia. *International Journal of Environmental Research and Public Health*, *16*(6), 1013. https://doi.org/10.3390/ijerph16061013
21. Tarigan, W. S. (2021). Analisis Regresi Spasial pada Indeks Pembangunan Manusia di Provinsi Sumatera Utara Tahun 2020. *Seminar Nasional Official Statistics*, *2021*(1), 403–408. https://doi.org/10.34123/semnasoffstat.v2021i1.896
22. Timmreck, T. C. (2002). *An introduction to epidemiology*. Jones & Bartlett Learning.
23. Vong, S., Khieu, V., Glass, O., Ly, S., Duong, V., Huy, R., Ngan, C., Wichmann, O., Letson, G. W., Margolis, H. S., & Buchy, P. (2010). Dengue Incidence in Urban and Rural Cambodia: Results from Population-Based Active Fever Surveillance, 2006–2008. *PLoS Neglected Tropical Diseases*, *4*(11), e903. https://doi.org/10.1371/journal.pntd.0000903

24. WHO. (2025). *Dengue and severe dengue*. https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue
25. Widyatama, E. F. (2017). *Faktor yang Berpengaruh Terhadap Kejadian Demam Berdarah Dengue Daerah Endemis di Wilayah Kerja Puskesmas Pare Kecamatan Pare Kabupaten Kediri*.
26. Wijirahayu, S., & Sukesi, T. W. (2019). Hubungan Kondisi Lingkungan Fisik dengan Kejadian Demam Berdarah Dengue di Wilayah Kerja Puskesmas Kalasan Kabupaten Sleman. *JURNAL KESEHATAN LINGKUNGAN INDONESIA*, *18*(1), 19. https://doi.org/10.14710/jkli.18.1.19-24
27. Zulheri, E. I., Asdi, Y., & Yozza, H. (2019). MODEL REGRESI SPASIAL LAG PADA KASUS PENYAKIT DEMAM BERDARAH DENGUE (DBD) DI SUMATRA UTARA TAHUN 2016. *Jurnal Matematika UNAND*, *8*(2), 59. https://doi.org/10.25077/jmu.8.2.59-66.2019