

GIS-Based Spatial Mapping of Dengue Hemorrhagic Fever Cases in Seyegan, Ngaglik 1, and Minggir Primary Healthcare Areas, Sleman Regency

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ABSTRACT

Introduction: Dengue hemorrhagic fever (DHF) remains a public health problem in Sleman Regency and requires location-based information to guide control priorities. This study aimed to map case distribution and analyze the spatial pattern of DHF exclusively within three selected primary health-care catchment areas representing the highest case counts in Sleman Regency.

Methods: A retrospective quantitative descriptive spatial study analyzed all 108 confirmed cases in these three selected areas (Seyegan, Ngaglik 1, and Minggir) using frequency distributions, incidence rates, point mapping, and Average Nearest Neighbor (ANN) in Microsoft Excel and ArcGIS 10.3.

Results: Of 423 cases across 25 primary health-care centers, Seyegan recorded 42 cases (IR 78.94/100,000 population), Ngaglik 1 recorded 33 cases (IR 60.59/100,000), and Minggir recorded 33 cases (IR 100.51/100,000); all three were classified as high-incidence areas. Based on ANN analysis, there was insufficient evidence to reject the assumption of spatial randomness in Seyegan (NNR 0.894913; $p=0.192616$), Ngaglik 1 (NNR 1.034989; $p=0.700593$), and Minggir (NNR 1.029359; $p=0.746962$). Regarding the distribution of reported cases, individuals aged 15–44 years (58.3%) and males (57.4%) accounted for the highest proportions; however, this does not necessarily indicate a higher risk as population denominators for these specific groups were not assessed. Meanwhile, the monthly rainfall–case pattern was nonlinear.

Conclusion: The different rankings produced by case counts and incidence rates emphasize the importance of population denominators when comparing disease burdens. GIS serves as a valuable tool for visualizing disease distribution in high-incidence areas; however, to directly determine intervention priorities and vector control, this spatial mapping must be further integrated with comprehensive entomological and environmental data.

Keywords: ArcGIS; Average Nearest Neighbor; Dengue hemorrhagic fever; Geographic information system; Spatial mapping

INTRODUCTION

Spatial mapping of Dengue Hemorrhagic Fever (DHF) cases using Geographic Information Systems in Sleman Regency is necessary to highlight variations in disease burden that are not visible in aggregate figures[1] [2][3]. DHF is a dengue virus infection primarily transmitted by *Aedes aegypti* and remains a significant health threat in tropical regions, influenced by vector, environmental, mobility, behavioral, and climate interactions [4][5] [6][7][8][9][10]. Sleman's geographical conditions, which combine urban, rural, and buffer zones, can create differences in settlement density, mosquito breeding sites, rainfall, and control

effectiveness across locations.

Geographic Information Systems (GIS) connect health data with coordinates, administrative boundaries, and environmental attributes to display case concentrations and support intervention targeting [11][12][13][14][15][5]. Previous research in Bangilan, Tuban, discovered a random pattern of DHF cases via Average Nearest Neighbor (ANN) analysis, despite entomological indicators showing high transmission risks[16][17][5][18]. Similarly, studies in Jepara indicated random spatial patterns and relationships with environmental

parameters[19][20][21], while ArcGIS Dashboard visualization in Sleman highlighted that maps and graphs can integrate multiple surveillance indicators into a single platform [22].

These previous studies suggest an information gap where interpreting spatial patterns must rigorously consider the scale of analysis, population denominators, environmental factors, and vector indicators. While several studies have visualized DHF distribution in Sleman, they have largely relied on descriptive point mapping or administrative boundaries without testing for the statistical significance of case clustering. This study addresses this specific knowledge gap by applying Average Nearest Neighbor (ANN) spatial statistics to quantitatively determine whether DHF cases in Sleman's highest-burden areas represent true statistically significant clusters or are merely random occurrences driven by dispersed household-level factors.

In the specific context of Sleman, where rapid suburbanization blends rural and urban landscapes, ANN analysis is critical because visual point maps can often be misleading, creating a false impression of "hotspots" in densely populated villages. The novelty of this study lies in its strict comparative approach, integrating absolute case counts with population-adjusted incidence rates (IR) and advanced statistical ANN analysis within three selected high-incidence primary healthcare areas. Ultimately, this research aims to provide a functional, evidence-based framework that primary health centers can replicate to move beyond basic visualization enabling them to systematically verify true spatial patterns, update operational maps, and direct epidemiological investigations and mosquito eradication responses more effectively. This study aims to: 1) identify case distribution and calculate the Incidence Rates (IR) to highlight differences in disease burden; 2) visualize the spatial point spread of DHF cases; 3) statistically analyze the spatial distribution patterns using Average Nearest Neighbor (ANN); and 4) describe the trends of DHF cases concerning monthly rainfall, age, and

gender. **Specifically, this analysis is exclusively focused on Seyegan, Ngaglik 1, and Minggircethe three primary health-care catchment areas with the highest DHF case counts in Sleman Regency.** Ultimately, this research aims to provide evidence-based spatial information that primary health centers can utilize to verify high-incidence villages and systematically direct epidemiological investigations and case responses more effectively.

METHOD

Research Type

This research utilized a quantitative descriptive study design with a retrospective spatial approach using secondary data. The events analyzed were confirmed DHF cases from January to December 2025.

Population and Sample/Informants

The study population comprised 108 confirmed DHF cases recorded in 2025 across three primary healthcare center (Puskesmas) catchment areas in Sleman Regency: Seyegan, Ngaglik 1, and Minggir. Total sampling was applied, incorporating all 108 confirmed cases as the sample without random selection. These three specific areas were purposefully selected because they reported the highest absolute case numbers in the regency. Although incidence rates (IR) are typically used to assess relative disease risk, absolute case counts were chosen as the primary selection criterion in this study to directly reflect the actual volume of the disease burden and the heavy operational strain on epidemiological response resources (such as field investigations and vector control) at these specific facilities.

To calculate the Incidence Rates, population denominators for each catchment area were obtained from the 2025 demographic registry provided by the Sleman Regency Health Office and the Central Bureau of Statistics (BPS). These population figures represent the total estimated residents living within the administrative boundaries of each respective primary healthcare center.

It is important to acknowledge that purposefully selecting only the three highest-burden areas introduces selection bias, as the sample represents the peak extremes of DHF distribution rather than the average regency profile. Consequently, the spatial patterns, environmental interactions, and demographic trends observed in Seyegan, Ngaglik 1, and Minggir cannot be generalized to the entire Sleman Regency, particularly to areas with low or moderate DHF transmission.

Research Location

The study was conducted utilizing data from the Sleman Regency Health Office and the working areas of Seyegan, Ngaglik 1, and Minggir Primary Healthcare Centers.

Instrumentation or Tools

Data on DHF cases, patient age, gender, and residential coordinates were obtained from health office surveillance reports. Administrative boundary shapefiles were used as base maps for case points, and rainfall data was sourced from the Meteorology, Climatology, and Geophysical Agency (BMKG) [3]. Data processing and analysis were performed using Microsoft Excel and ArcGIS 10.3.

Data Collection Procedures

Data collection, verification, and processing were conducted from January to March 2026. Researchers initially gathered DHF data from 25 primary healthcare centers for the year 2025, checked for duplications, and identified the three centers with the highest cases. Addresses and coordinate points for the 108 cases were then aligned with administrative boundaries and organized in Microsoft Excel spreadsheets.

Data Analysis

Prior to analysis, residential coordinates for all 108 cases were manually geocoded. Addresses obtained from the surveillance reports were plotted using digital mapping platforms (e.g., Google Maps) to extract precise latitude and longitude coordinates. The accuracy of these coordinate points was verified against the administrative village boundary shapefiles to ensure they fell

within the correct catchment area of the respective primary healthcare center. No coordinates were missing; thus, all 108 cases were included in the spatial analysis.

Descriptive statistics were employed to calculate case frequencies and percentages. The Incidence Rate (IR) was calculated by dividing the number of cases by the population, then multiplied by 100,000. Following the Ministry of Health of the Republic of Indonesia guidelines [6], the IR was categorized as low (<20), moderate ($20-55$), or high (>55).

Spatial patterns were analyzed using the Average Nearest Neighbor (ANN) tool in ArcGIS 10.3. The spatial data was projected using the WGS 1984 coordinate reference system. The ANN calculation utilized the Euclidean distance measurement method to compute the distance between a feature and its nearest neighbor. The study area for the ANN calculation was defined strictly by the administrative boundary polygons of each respective primary healthcare center. A statistical significance level of 95% ($\alpha = 0.05$) was employed; a p -value < 0.05 with a z -score < -1.96 indicated significant clustering, while a p -value < 0.05 with a z -score > 1.96 indicated significant dispersion.

Finally, demographic variables (age and gender) and environmental variables (trends regarding monthly rainfall) were analyzed descriptively.

Ethical Approval

This research was conducted following the acquisition of ethical clearance from this research was conducted following the acquisition of ethical clearance from the Health Research Ethics Committee of Politeknik Kesehatan Bhakti Setya Indonesia (Approval Number:005/S.Permoh.RMIK/Dir-POLBS1/2026). Formal permission to utilize secondary health surveillance data, including medical records and patient addresses, was obtained from the Sleman Regency Health

Office and the respective primary healthcare centers.

The study maintained strict confidentiality by only presenting aggregate demographic data and regional maps without displaying names, medical record numbers, or any personal identities of the patients. Because the study involved mapping residential coordinates,

spatial confidentiality was strictly protected; case points visualized on the maps were presented at a regional scale without high-resolution zoom or identifiable street-level basemaps, ensuring that individual household locations could not be retraced or identified by the public

RESULT

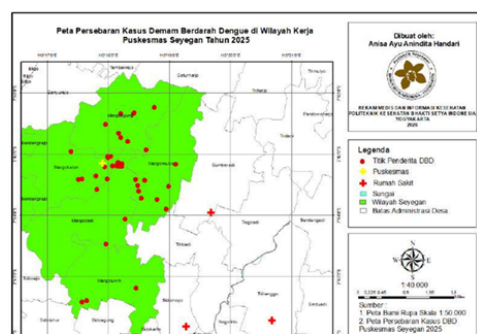
In 2025, a total of 423 DHF cases were documented across 25 primary healthcare center working areas in Sleman Regency. The

three regions with the highest case counts were Seyegan with 42 cases (9.93%), Ngaglik 1 with 33 cases (7.80%), and Minggir with 33 cases (7.80%). 5)

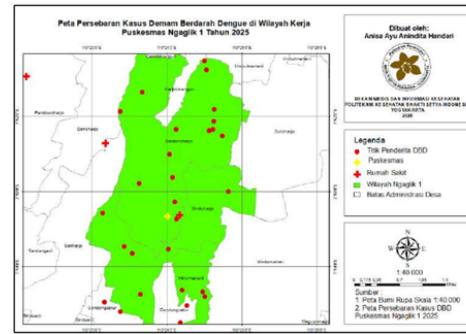
Table 1. Distribution of cases and DHF incidence rate in three primary healthcare centers in Sleman Regency, 2025

Primary Healthcare Center	Cases (n)	Population	IR/100,000	Category	Village with Most Cases
Seyegan	42	53,203	78.94	High	Margodadi and Margomulyo (11 each)
Ngaglik 1	33	54,459	60.59	High	Sardonoharjo (15)
Minggir	33	32,832	100.51	High	Sendangmulyo (10)

A. Puskesmas Seyegan



B. Puskesmas Ngaglik 1



C. Puskesmas Minggir

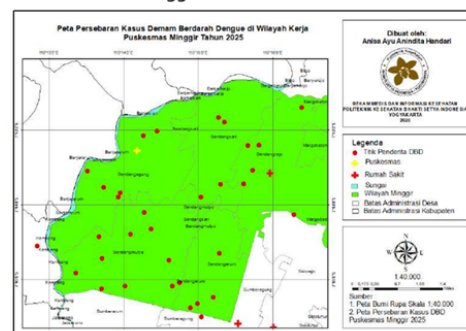


Figure 1. High-resolution distribution map of DHF case points and primary healthcare center administrative boundaries (A: Seyegan, B: Ngaglik 1, C: Minggir) in Sleman Regency, 2025.

The spatial mapping demonstrated that case points were distributed across each working area, with descriptive concentrations visible in certain villages. Seyegan's cases were more prominent in Margodadi and Margomulyo, Ngaglik 1's in Sardonoarjo, and Minggir's in Sendangmulyo.

Regarding spatial boundaries, a visual assessment of the map reveals several case points located marginally outside the

primary administrative boundaries of the healthcare centers (particularly in Ngaglik 1). Following coordinate verification, it was confirmed that these points are not geocoding errors. Instead, they represent actual residential locations of patients whose registered domicile or initial reporting facility falls under the jurisdiction of the respective primary healthcare center, despite their geographic location intersecting with the buffer zones of neighboring sub-districts.

Table 2. Average Nearest Neighbor analysis results for DHF cases

Primary Healthcare Center	Observed mean distance (m)	Expected mean distance (m)	NNR	z-score	p-value	Interpretation
Seyegan	291.0392	325.2150	0.894913	-1.302878	0.192616	Random; not significant
Ngaglik 1	403.6131	389.9685	1.034989	0.384520	0.700593	Random; not significant
Minggir	498.7139	484.4898	1.029359	0.322648	0.746962	Random; not significant

The ANN results revealed that the observed point distributions in all three regions did not significantly differ from a theoretical model of Complete Spatial Randomness (CSR). Although Seyegan's NNR (0.894913) descriptively indicated a tendency to cluster, the z-score (-1.302878) and p-value (0.192616)

lacked sufficient statistical evidence to reject the null hypothesis of spatial randomness, meaning it cannot be declared a statistically significant cluster.

Table 3. Distribution of DHF cases based on age group and gender

Primary Healthcare Center	0–4 years	5–14 years	15–44 years	≥45 years	Male	Female
Seyegan	5	5	23	9	26	16
Ngaglik 1	0	0	26	7	18	15
Minggir	0	4	14	15	18	15
Total	5	9	63	31	62	46

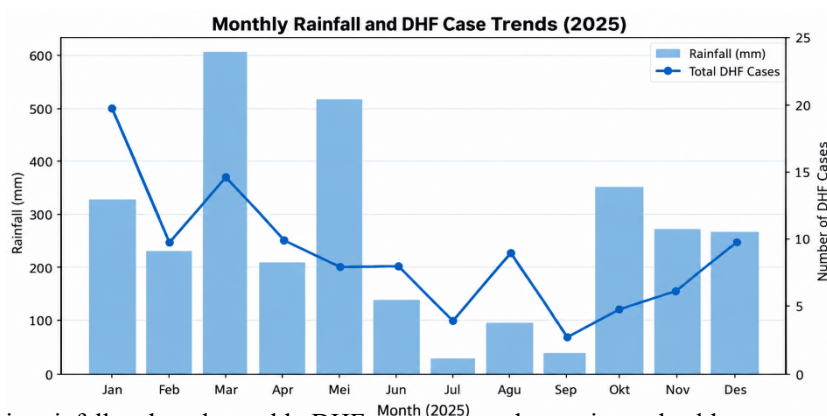


Figure 2. Trends in rainfall and total monthly DHF cases across three primary healthcare center working areas in 2025

DISCUSSION

Interpretation of Key Findings

Our study highlights that prioritizing regions solely by case counts yields different results than using Incidence Rates (IR). Seyegan possessed the highest total case count, indicating high service volume demands, whereas Minggir recorded the highest IR owing to its smaller population size, marking a higher relative risk.

Furthermore, interpreting spatial maps requires a clear distinction between visual descriptive concentrations and statistically significant spatial clustering. Descriptively, visual observation of the point maps suggested concentrated case groupings in specific villages, such as Margodadi in Seyegan and Sardonoarjo in Ngaglik 1. However, the global Average Nearest Neighbor (ANN) analysis revealed that these apparent concentrations were not statistically significant spatial clusters. Instead, the overall point distributions did not significantly deviate from Complete Spatial Randomness (CSR) across all three working areas.

This statistical randomness suggests that on a macro (catchment area) scale, DHF transmission is not exclusively centralized in one dominant hotspot. Instead, risk factors appear to be dispersed at the household level across the region. Nevertheless, while the global spatial pattern is random, localized epidemiological clusters may still exist at the neighborhood level. The visually concentrated areas on the maps likely point to micro-environments where localized mosquito breeding sites or high population density temporarily facilitate transmission, warranting targeted field epidemiological investigations (PE) by primary healthcare staff.

Additionally, the majority of cases affecting the productive age group (15–44

years) and males likely correlates to higher mobility and varied environmental exposures beyond their immediate residential coordinates, further contributing to the dispersed pattern of household infections.

Comparison with Previous Studies

These findings strongly support epidemiological tenets advocating the combined use of absolute and relative indicators for mapping disease burdens, as similarly emphasized by Istiqlala (8) and Ramadhani et al. (9), and further supported by recent national spatial studies [4][5][23]. The random ANN spatial patterns observed align closely with studies conducted in Bangilan and Jepara, which also found random distributions at similar regional scales despite high transmission potentials[16][20][24][25]. Furthermore, the dominance of DHF in the productive-aged and male demographic corroborates findings by Khoisiah et al. [26], emphasizing mobility as a probable key factor in dengue exposure[26][27][9]. The non-linear relationship observed between rainfall, density, and cases corresponds with studies by Putra & Lestari[21] and Girsang et al.[28]. The non-linear relationship observed between rainfall and cases corresponds with studies by Putra & Lestari [21] and Girsang et al. [28], demonstrating that climate factors do not function independently but interact with complex localized environmental and behavioral factors [28] [29][30][31].

Limitations and Cautions

Several limitations must be acknowledged. First, an in-depth spatial analysis was solely applied to the top three primary healthcare centers, meaning it does not holistically represent the variations across all of Sleman Regency. Second, the ANN methodology utilized point coordinates without factoring in the underlying distribution of the at-risk population, and it strictly measured global patterns without testing for local clusters. Third, the evaluations of rainfall and population density were entirely descriptive; they lacked time-lag correlational testing and did not control for confounding variables. Consequently, findings should primarily

inform field investigations rather than serve as definitive causal estimates.

Recommendations for Future Research

To overcome these constraints, future research should expand the spatial framework to include all healthcare centers in the regency. Implementing advanced spatio-temporal modeling and local cluster analysis methods such as Kernel Density Estimation or spatial scan statistics would provide a more granular understanding of disease pockets. Furthermore, studies should integrate detailed vector and environmental indicators with time-lag modeling while continuing to ensure stringent patient confidentiality.

CONCLUSION

This study mapped the case distribution and analyzed the spatial pattern of DHF exclusively within Seyegan, Ngaglik 1, and Minggir the three primary healthcare catchment areas with the highest case counts in Sleman Regency. The results demonstrated a heterogeneous DHF burden; Seyegan experienced the highest absolute case volume, whereas Minggir exhibited the highest Incidence Rate, though all three were categorized as high-IR zones. Crucially, the Average Nearest Neighbor analysis revealed that the global spatial patterns within these selected areas did not significantly differ from spatial randomness, despite descriptive visual concentrations in certain villages. These findings underscore the practical importance of integrating absolute case counts, relative incidence, and spatial statistics to prevent the misinterpretation of raw visual maps. Rather than serving as a standalone solution for optimizing interventions, GIS functions as a valuable exploratory surveillance tool. It must be integrated with field epidemiological data to systematically investigate potential localized transmission clusters.

Although this study offers insightful information on GIS-based operational surveillance, several limitations are acknowledged. Specifically, the findings are limited to the three selected high-burden areas and cannot be generalized to the entire Sleman Regency. Furthermore, the analysis lacked local spatio-temporal cluster testing and relied on descriptive assessments of environmental

variables. Future studies should expand to regency-wide coverage and employ local spatio-temporal cluster analysis, incorporating robust entomological data to better understand dengue transmission dynamics and effectively guide localized vector control interventions.

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