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GIS-Based Spatial Temporal Analysis And Priority Scoring For Malaria Control In Nabire Regency

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ABSTRACT

Malaria remains a critical public health challenge in Nabire Regency, Central Papua, where escalating incidence rates necessitate targeted control strategies. Currently, routine surveillance data are predominantly presented in tabular formats, inherently limiting their utility for spatially informed decision-making. Addressing this gap, this study analyzes the spatial-temporal dynamics of malaria transmission and develops a novel Malaria Spatial Priority Index (MSPI) a GIS-based multi-criteria priority scoring model to identify high-risk intervention zones. A quantitative descriptive-analytical framework was applied to surveillance data spanning 2018- 2025, integrating epidemiological indicators Annual Parasite Incidence (API), Annual Blood Examination Rate (ABER), and Slide Positivity Rate (SPR) with localized village and Puskesmas spatial parameters. The results reveal a severe intensification of the malaria burden in 2025, characterized by a 76.85% surge in positive cases (from 3,274 to 5,790) alongside synchronized increases in API and SPR. Spatial risk stratification using the MSPI identified Samabusa and Legari as very high-priority service areas, while Kalibobo, Wami Jaya, and Sanoba emerged as the primary transmission hotspots at the village level. Crucially, the spatial distribution demonstrated that administrative boundaries do not uniformly dictate disease risk. This study concludes that synthesizing routine epidemiological metrics with GIS-based spatial prioritization successfully transforms descriptive tabular data into operational spatial intelligence. This novel MSPI framework provides local health authorities with a robust, evidence-based decision-support tool to optimize resource allocation and dismantle localized transmission chains in highly endemic regions.

INTRODUCTION

Malaria remains a major public health problem in Indonesia, particularly in Papua and Central Papua, where transmission rates remain higher than in most other provinces (Fadilah dkk., 2022; Hasifah & Rinenggantyas, 2026; Syahrani dkk., 2025) . Previous studies have reported substantial spatial heterogeneity of malaria transmission in Papua, indicating that malaria risk varies across locations and requires area-specific intervention strategies. Therefore, understanding the spatial and temporal distribution of malaria is essential for strengthening surveillance systems and supporting evidence-based malaria control programs (Djaafara dkk., 2025)

Nabire Regency is one of the malaria-endemic areas in Central Papua Province. Malaria surveillance data showed an increase in positive malaria cases from 3,274 cases in 2024 to 5,790 cases in 2025. During the same period, the Annual Parasite Incidence (API) increased from 19.35 to 33.46 per 1,000 population, while the Slide Positivity Rate (SPR) increased from 3.60% to 5.72%. These trends indicate an increasing malaria burden and highlight the need for more effective approaches to identify high-risk areas and prioritize interventions. However, routine surveillance data are generally presented in tabular reports, limiting the identification of spatial patterns and priority intervention areas (Dinas Kesehatan Kabupaten Nabire, 2025a; Ridha dkk., 2022). Geographic Information System (GIS) has been widely applied for disease mapping, hotspot identification, risk assessment, and surveillance enhancement by integrating epidemiological and spatial (Ramírez Montalván dkk., 2025). In malaria control, GIS can transform routine surveillance data into spatial information that supports evidence-based decision-making and targeted intervention planning (Cissoko dkk., 2025; Fahmi dkk., 2022).

Previous studies have investigated malaria transmission using spatial mapping, spatial-temporal clustering, environmental risk assessment, and machine learning approaches for diagnosis and prediction (Djaafara dkk., 2025; Fadilah dkk., 2022; Setyawan dkk., 2022). While these studies have significantly contributed to understanding malaria epidemiology, most remain focused on disease distribution patterns, environmental determinants, or predictive modeling. Limited studies have translated routine malaria surveillance data into an operational decision-support framework that directly supports intervention prioritization at the local health service level. In particular, evidence from Nabire Regency remains scarce despite the increasing malaria burden and the urgent need for geographically targeted

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control strategies. Consequently, a practical framework capable of integrating epidemiological indicators, spatial information, and intervention prioritization is required to strengthen evidence-based malaria control.

This study addresses the identified gap by integrating routine malaria surveillance data, epidemiological indicators (API, ABER, and SPR), village/sub-district case concentration, and Puskesmas service area data into a spatial decision-support framework. The novelty of this study lies in the development of the Malaria Spatial Priority Index (MSPI), a direct and operational prioritization model that translates complex epidemiological datasets into actionable spatial intelligence.

Therefore, this study aims to analyze the spatial-temporal distribution of malaria cases in Nabire Regency and identify priority areas for malaria control using the GIS-based MSPI model. The findings are expected to support intervention prioritization, resource allocation, and evidence-based malaria control strategies in endemic areas.

LITERATURE REVIEW

Malaria remains a major public health challenge in Papua and Central Papua, where transmission rates persistently exceed those in many other regions of Indonesia. Effective malaria control fundamentally depends on robust surveillance systems that provide reliable data on disease occurrence, transmission intensity, and intervention outcomes. Epidemiological indicators, including Annual Parasite Incidence (API), Annual Blood Examination Rate (ABER), and Slide Positivity Rate (SPR), serve as standard metrics to assess malaria burden, examination coverage, and positivity rates (Ashar, Lauchan, dkk., 2025; Ashar, Safira, dkk., 2025; Djaafara dkk., 2025; WHO, 2024).

Consequently, Geographic Information System (GIS) and spatial-temporal analysis have been extensively applied in health informatics to enhance disease mapping, risk assessment, hotspot identification, and location-based decision-making (Fahmi dkk., 2022; Haisoufi & Bouaiti, 2024; Nikolova & Aleksandrova, 2025; Ramírez Montalván dkk., 2025). Spatial-temporal analysis further strengthens this approach by examining disease variations across locations and time periods, allowing the identification of high-risk areas and transmission trends (Djaafara dkk., 2025; Herdianti and Munadi, 2025; Legendre dkk., 2023). Furthermore, recent advancements in decision-support frameworks and healthcare informatics have demonstrated the profound efficacy of computational models and priority scoring in optimizing public health strategies and resource allocation (Damanik dkk., 2025; Sahputra dkk., 2025; Zubaedah & Prasetyo, 2022).

To establish the novelty of this research within the broader landscape of health informatics and epidemiology, Table 1 categorizes recent methodological approaches in malaria research and delineates the specific position of the current study.

Table 1. Previous Studies and Research Position

No.	Research Theme	Selected Studies	Core Approach	Position of This Study (Novelty)
1	Spatial Transmission & Heterogeneity	(Djaafara dkk., 2025; Fadilah dkk., 2022)	National and regional routine epidemiological surveillance analysis.	Downscales transmission analysis to localized Puskesmas and village-level data specifically in Nabire Regency.
2	GIS Risk Mapping & Stratification	(Cissoko dkk., 2025; Fahmi dkk., 2022; Herdianti and Munadi, 2025)	Spatial risk modeling, clustering, and geo-epidemiological stratification.	Develops a direct, operational GIS priority scoring framework for localized intervention targets.
3	Environmental & Vector Analysis	(Tulak dkk., 2025)	Assessing climate and ecological predictors (e.g., NDVI, rainfall).	Prioritizes accessible epidemiological indicators (API, ABER, SPR) over environmental factors for rapid public health decision-making.
4	Computational Malaria Diagnostics	(Muhandisin & Azhar, 2022; Setyawan dkk., 2022)	Machine learning (e.g., ResNet50) and image processing for clinical blood cell classification.	Shifts the health informatics focus from clinical/laboratory diagnostics to geospatial population health management.

Table 1 synthesizes the methodological approaches of previous studies and highlights the specific research gap addressed by the current study. While existing literature has contributed significantly to understanding malaria transmission through broad regional surveillance, spatial clustering, environmental assessments, and clinical machine learning models, these studies predominantly remain at the macro-epidemiological or diagnostic level.

A critical gap persists in translating these advanced analytical concepts into operational, localized public health tools. Unlike previous studies that rely heavily on complex environmental predictors or national-scale datasets, this study develops a direct, district-level GIS priority scoring framework. By integrating accessible routine surveillance metricsspecifically absolute positive cases, API, SPR, and village-level case concentrations this research shifts the paradigm from descriptive epidemiology to an operational spatial decision-support model, designed to precisely target

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and allocate malaria control interventions within Nabire Regency.

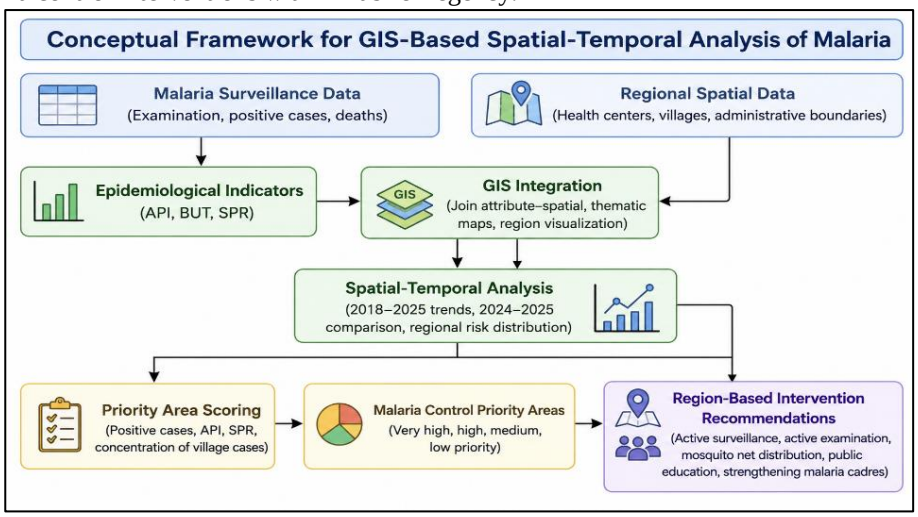

Figure 1. Conceptual Framework of GIS-Based Spatial-Temporal Malaria Analysis

Figure 1 illustrates the conceptual relationship between malaria surveillance data, epidemiological indicators, spatial information, GIS integration, spatial-temporal analysis, priority scoring, and intervention recommendations. Malaria surveillance data, including malaria examinations, positive cases, malaria-related deaths, and reporting locations, serve as the primary input of the framework. These variables are commonly used in malaria surveillance systems to monitor transmission dynamics and evaluate intervention outcomes (Kemenkes RI, 2022)).

The surveillance data are used to generate epidemiological indicators, namely Annual Parasite Incidence (API), Annual Blood Examination Rate (ABER), and Slide Positivity Rate (SPR), which are widely applied to assess malaria risk, examination coverage, and positivity rates (Djaafara dkk., 2025; Fahmi dkk., 2022). These indicators are subsequently integrated with spatial data consisting of administrative boundaries, Puskesmas service areas, and village/sub-district units.

The integration of epidemiological and spatial data through Geographic Information System (GIS) enables the analysis of malaria distribution patterns across space and time. GIS has been extensively utilized in disease mapping, hotspot identification, risk assessment, and spatial decision support (Haisoufi & Bouaiti, 2024; Ramírez Montalván dkk., 2025). The resulting spatial-temporal information is used to identify high-risk areas and support priority scoring based on positive malaria cases, epidemiological indicators, and village/sub-district case concentration.

The framework ultimately produces a classification of malaria control priorities into very high, high, medium, and low categories. These priority classifications provide a basis for evidence-based intervention planning, including surveillance strengthening, active case detection, vector control, community education, and location-specific malaria control strategies (Cissoko dkk., 2025). Therefore, the framework transforms routine surveillance data into operational spatial information that supports malaria control decision-making in Nabire Regency.

The conceptual framework was adapted from previous studies on GIS-based disease surveillance, spatial epidemiology, and health decision-support systems that emphasize the integration of epidemiological indicators with spatial information for intervention planning (Fahmi dkk., 2022; Haisoufi & Bouaiti, 2024; Ramírez Montalván dkk., 2025).

METHOD

This study employed a quantitative descriptive-analytical approach utilizing Geographic Information System (GIS)-based spatial-temporal modeling to evaluate malaria distribution patterns and identify priority intervention zones in Nabire Regency, Central Papua. The spatial-temporal framework was selected to transform abstract epidemiological data into operational geographical intelligence, facilitating targeted, area-based intervention (Legendre dkk., 2023; Mwangungulu dkk., 2023; Ngadino dkk., 2024). The analysis scrutinized malaria surveillance data spanning 2018 to 2025, with a primary analytical focus on the 2024–2025 cross-section due to a severe observed escalation in transmission intensity. The spatial units of analysis comprised the 18 Puskesmas service areas and localized village/sub-district administrative boundaries.

The research synthesized attribute and spatial datasets extracted from the national Esismal/SISMAL V3 database, localized malaria program reports, and regional administrative spatial repositories (Dinas Kesehatan Kabupaten Nabire, 2025b). As detailed in Table 2, the attribute variables encompassed total malaria examinations, confirmed positive cases, malaria-related mortality, and localized case contributions, all adhering rigorously to the Indonesian Ministry of Health surveillance standards (Kemenkes RI, 2022). Concurrently, the spatial data architecture included digitized administrative boundaries and Puskesmas service area polygons to serve as the foundational layers for thematic

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mapping.

Table 2. Research Data Types and Sources

No.	Data Type	Source	Function
1	Examinations and positive cases, 2018–2025	Esismal/SISMAL V3	Trend analysis
2	API, ABER, SPR, and deaths	Malaria program reports	Indicator analysis
3	Puskesmas service area data	Nabire Health Office	Puskesmas-level mapping
4	Village/sub-district case data	Malaria program reports	Case concentration analysis
5	Administrative spatial data	Spatial data/QGIS	Thematic and priority mapping

The analytical workflow progressed chronologically through data validation, attribute-spatial integration, epidemiological indicator computation, temporal trend analysis, thematic mapping, and multi-criteria priority scoring (Figure 2). Data cleaning ensured the topological consistency and standardization of administrative nomenclature. Following validation, three primary epidemiological indicators—Annual Parasite Incidence (API), Annual Blood Examination Rate (ABER), and Slide Positivity Rate (SPR)—were calculated to quantify transmission incidence, testing coverage, and infection positivity, respectively (Aisyah dkk., 2024; Fadilah dkk., 2022). The computations utilized the following standard epidemiological equations:

$$API = Positive\ Cases/Population \times 1000 \qquad (1)$$

$$ABER = \frac{Examinations}{Population} \times 100 \qquad (2)$$

$$SPR = \frac{Positive\ Cases}{Examinations} \times 100 \qquad (3)$$

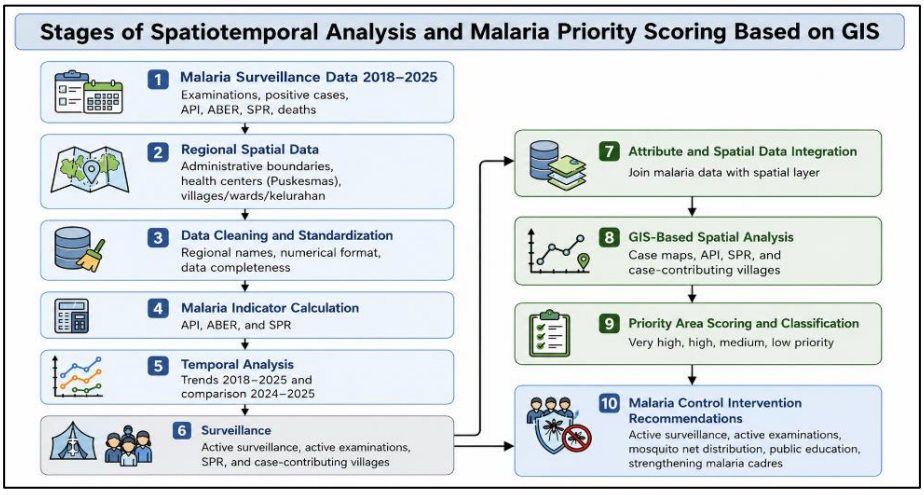

Figure 2. Stages of GIS-Based Spatial-Temporal Analysis and Malaria Priority Scoring

The calculated indicators were subsequently joined with the spatial layers using QGIS to generate continuous spatial-temporal outputs. To transcend descriptive mapping and provide operational decision support, a novel composite model termed the Malaria Spatial Priority Index (MSPI) was developed utilizing four variables: absolute confirmed cases, API, SPR, and village-level case concentration (Table 3). Each variable was normalized into a discrete score ranging from 1 to 3. In the absence of an expert-elicited weighting technique such as the Analytical Hierarchy Process (AHP), this study applied an equal-weighting heuristic approach. This method is firmly grounded in the public health precautionary principle, positing that transmission incidence (API), infection positivity (SPR), and absolute case volume are equally critical dimensions of malaria risk in highly endemic settings (Fransisca dkk., 2025; Nikolova & Aleksandrova, 2025; Yadav & Sharma, 2022). The equal-weighting strategy was intentionally selected to ensure methodological transparency and ease of implementation by local public health practitioners. Since the primary objective of the MSPI is operational prioritization rather than predictive modeling, assigning equal weights minimizes computational complexity and facilitates routine application within resource-limited health systems. Similar approaches have been adopted in public health prioritization frameworks when empirical evidence for differential weighting is unavailable (Fahmi dkk., 2022; Stresman dkk., 2025; Yadav & Sharma, 2022). The aggregated MSPI scores dictated the final classification of each region into very high, high, medium, or low priority categories (Table 4), thereby directly informing evidence-based resource allocation.

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To provide a clearer understanding of the priority scoring procedure, Figure 3 illustrates the workflow of the Malaria Spatial Priority Index (MSPI) development. The framework integrates epidemiological indicators, including positive malaria cases, API, SPR, and village-level case concentration, into a composite scoring model for identifying malaria intervention priorities.

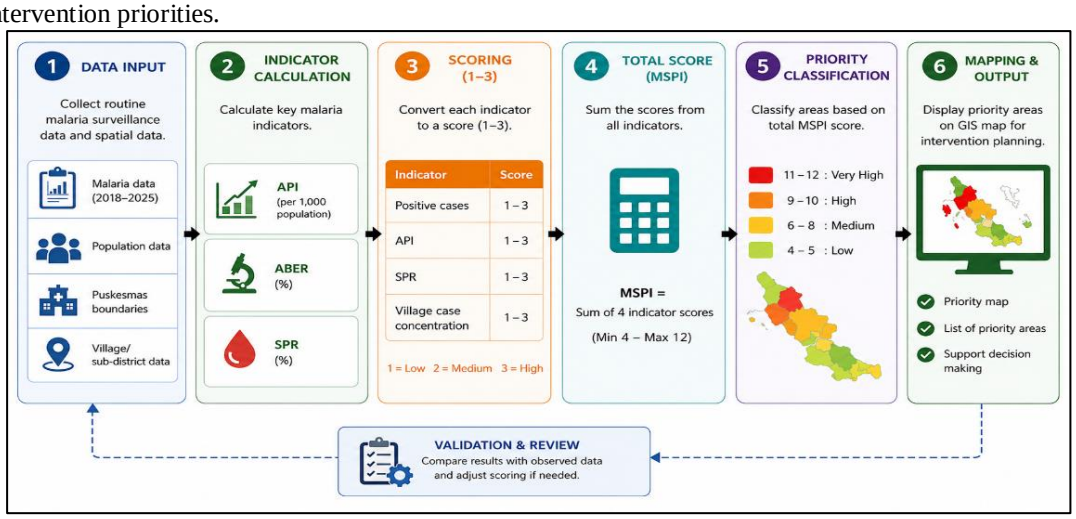

Figure 3. Workflow of Malaria Spatial Priority Index (MSPI) Development

As illustrated in Figure 3, the MSPI development process begins with the collection of malaria surveillance and spatial data. Epidemiological indicators are subsequently calculated and converted into standardized scores ranging from 1 to 3. The scores are aggregated to generate the MSPI value, which is then classified into four priority levels: very high, high, medium, and low. The resulting priority categories are visualized through GIS-based thematic maps to support evidence-based malaria intervention planning.

To standardize the prioritization process, each indicator was converted into a discrete score ranging from 1 to 3 based on its relative contribution to malaria transmission risk. The classification thresholds were determined using a combination of national malaria surveillance indicators, distribution characteristics of the Nabire malaria dataset, and practical considerations for public health intervention planning. Higher scores indicate greater epidemiological significance and a higher need for immediate malaria control actions. The aggregated MSPI scores were subsequently used to classify each area into intervention priority categories.

Table 3. Scoring Criteria for Malaria Control Priority Areas

Indicator	Score 1	Score 2	Score 3
Positive malaria cases	<100 cases	100–300 cases	>300 cases
API	<5 per 1,000 population	5–50 per 1,000 population	>50 per 1,000 population
SPR	<5%	5–10%	>10%
Village/sub-district case concentration	Not included in top 15	Ranked 11–15	Ranked 1–10

As shown in Table 3, positive malaria cases, API, SPR, and village-level case concentration were selected because they collectively represent disease burden, transmission intensity, infection positivity, and spatial clustering. The scoring system enables multiple epidemiological dimensions to be integrated into a single operational framework for malaria intervention prioritization.

Table 4. Priority Categories Based on Total Score

Total Score	Priority Category	Interpretation
11–12	Very high priority	Requires intensive and immediate intervention
9–10	High priority	Requires strengthened surveillance and active intervention
6–8	Medium priority	Requires routine monitoring and prevention
4–5	Low priority	Requires periodic monitoring

The final priority categories were derived from cumulative MSPI scores, where higher scores indicate greater malaria risk and intervention urgency. Areas with higher scores require more intensive control efforts, while lower-scoring areas require routine monitoring and prevention.

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RESULT

Malaria surveillance data in Nabire Regency exhibited dynamic trends between 2018 and 2025, culminating in a marked escalation of the disease burden in the final year of observation. The annual number of malaria examinations increased from 35,230 in 2018 to 102,064 in 2024, followed by a marginal decrease to 101,281 in 2025. Despite this slight reduction, confirmed positive malaria cases surged sharply from 3,274 in 2024 to 5,790 in 2025, representing a 76.85% rise. This increase was accompanied by a deterioration of key epidemiological indicators. The Annual Parasite Incidence (API) increased from 19.35 to 33.46 per 1,000 population (a 72.92% increase), while the Slide Positivity Rate (SPR) escalated from 3.60% to 5.72%. Malaria-related mortality also intensified, rising from three deaths in 2024 to eight deaths in 2025. In contrast, the Annual Blood Examination Rate (ABER) demonstrated an overall upward trajectory throughout the study period, increasing from 35.00% in 2018 to reach 58.53% in 2025.

The observed increase in malaria burden was not solely attributable to changes in surveillance coverage. Although the number of examinations declined slightly by 0.77% between 2024 and 2025, positive malaria cases increased by 76.85%, accompanied by simultaneous increases in API and SPR. This pattern suggests a genuine intensification of malaria transmission rather than an artifact of expanded testing activities. The concurrent rise in mortality further indicates that malaria remained a significant public health threat in Nabire Regency during 2025, requiring strengthened surveillance and targeted intervention efforts.

Table 5. Malaria Indicator Trends in Nabire Regency from 2018 to 2025

Year	Examinations	Positive Cases	API	ABER (%)	SPR (%)	Deaths
2018	35,230	2,307	22.93	35.00	5.30	4
2019	48,293	2,795	20.24	34.90	5.92	6
2020	35,543	2,360	14.98	22.55	6.65	2
2021	41,198	2,465	13.89	23.22	6.03	2
2022	61,455	3,499	21.58	37.90	5.74	5
2023	66,651	3,602	20.81	40.90	5.40	0
2024	102,064	3,274	19.35	50.40	3.60	3
2025	101,281	5,790	33.46	58.53	5.72	8

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b)

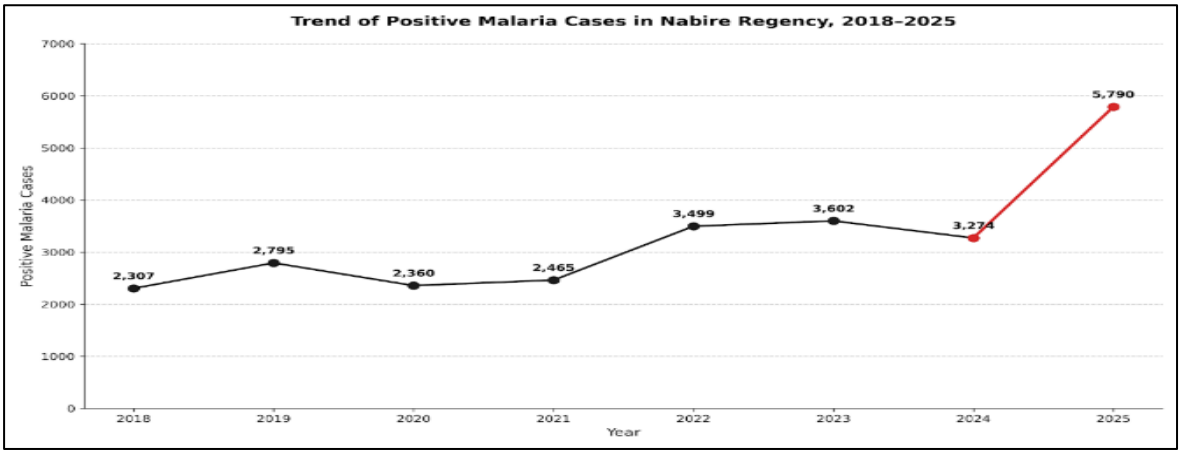

Figure 4. Trend of Positive Malaria Cases in Nabire Regency from 2018 to 2025

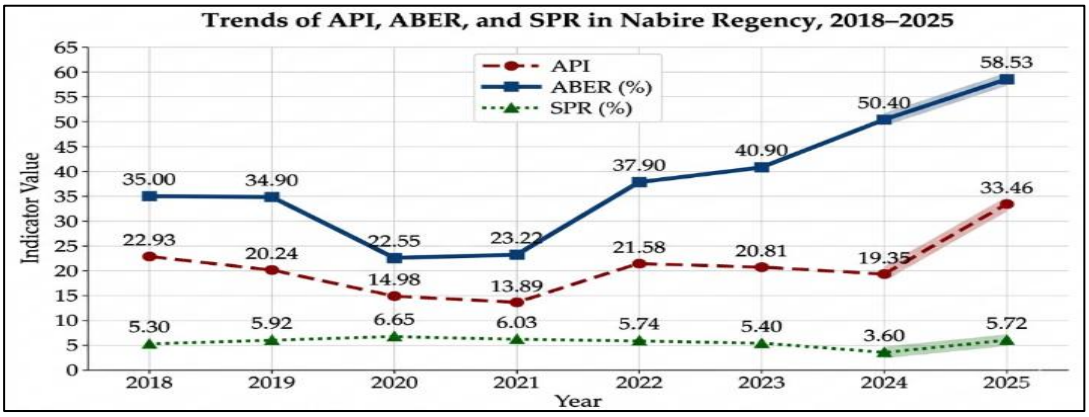

Figure 5. Trends of API, ABER, and SPR in Nabire Regency from 2018 to 2025

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Table 6. Comparison of Malaria Indicators in Nabire Regency between 2024 and 2025

Indicator	2024	2025	Change	Percentage Change
Examinations	102,064	101,281	-783	-0.77%
Positive cases	3,274	5,790	+2,516	+76.85%
API	19.35	33.46	+14.11	+72.92%
ABER	50.40	58.53	+8.13	+16.13%
SPR	3.60	5.72	+2.12	+58.89%
Malaria deaths	3	8	+5	+166.67%

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b).

The substantial increase in positive cases and API between 2024 and 2025 indicates that malaria transmission intensified beyond the effect of examination coverage expansion alone. Although the number of examinations slightly decreased by 0.77%, positive cases increased by 76.85%, resulting in a marked rise in both API and SPR. This pattern suggests the existence of active transmission clusters that require immediate epidemiological investigation and geographically targeted interventions.

Following the temporal evaluation, spatial analysis of the 2025 data revealed considerable heterogeneity in the distribution of malaria indicators across the 18 Puskesmas service areas. Puskesmas Wami recorded the highest API value at 139 per 1,000 population, followed by SP3 Topo Jaya (100) and Mambor (89). In terms of absolute positive cases, Puskesmas Samabusa reported the highest burden with 704 cases, followed by Legari (410) and SP 1 Kalibumi (353). The SPR distribution exhibited a distinct pattern, with Puskesmas Siriwo recording the highest positivity rate at 23%, followed by Samabusa (17%) and Kalibobo (15%).

Table 7. Distribution of Malaria Indicators by Puskesmas/Health Facility in 2025

No.	Puskesmas/Health Facility	Population	Examinations	Positive Cases	API	SPR (%)	ABER (%)
1	Puskesmas Wami	1,536	4,734	214	139	5	308
2	Puskesmas SP3 Topo Jaya	2,010	2,265	201	100	9	113
3	Puskesmas Mambor	851	2,266	76	89	3	266
4	Puskesmas Samabusa	9,198	4,257	704	77	17	46
5	Puskesmas Legari	5,395	5,492	410	76	7	102
6	Puskesmas Yaro	4,692	3,903	313	67	8	83
7	Puskesmas Topo	1,773	1,396	110	62	8	79
8	Puskesmas Wapoga	503	592	30	60	5	118
9	Puskesmas Siriwo	1,066	253	58	54	23	24
10	Puskesmas Yeretuar	621	1,807	27	43	1	291
11	Puskesmas Bawei	475	2,793	20	42	1	588
12	Puskesmas Maniwo	450	952	16	36	2	212
13	Puskesmas Karadiri	4,836	3,310	152	31	5	68
14	Puskesmas Napan	1,471	1,604	46	31	3	109
15	Puskesmas SP 1 Kalibumi	11,712	6,390	353	30	6	55
16	Puskesmas Sanoba	7,048	1,862	206	29	11	26
17	Puskesmas Kalibobo	12,438	1,680	248	20	15	14
18	Puskesmas SP3 Wadio	3,404	621	61	18	10	18

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b)

Table 7 presents the distribution of malaria indicators across Puskesmas service areas in Nabire Regency in 2025. The findings indicate substantial variation in malaria burden and transmission intensity among service areas. Wami recorded the highest API value (139 per 1,000 population), followed by SP3 Topo Jaya (100) and Mambor (89). In contrast, Samabusa reported the highest number of positive cases (704), followed by Legari (410) and SP 1 Kalibumi (353). These results demonstrate that areas with the highest incidence rates were not always the same areas with the highest absolute number of malaria cases.

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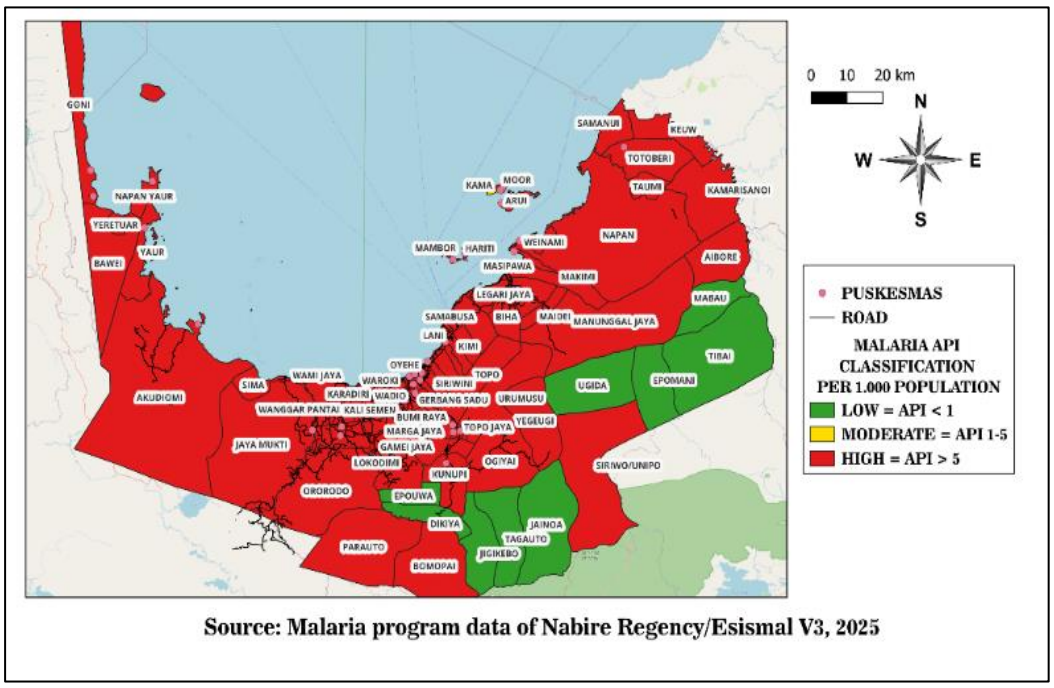
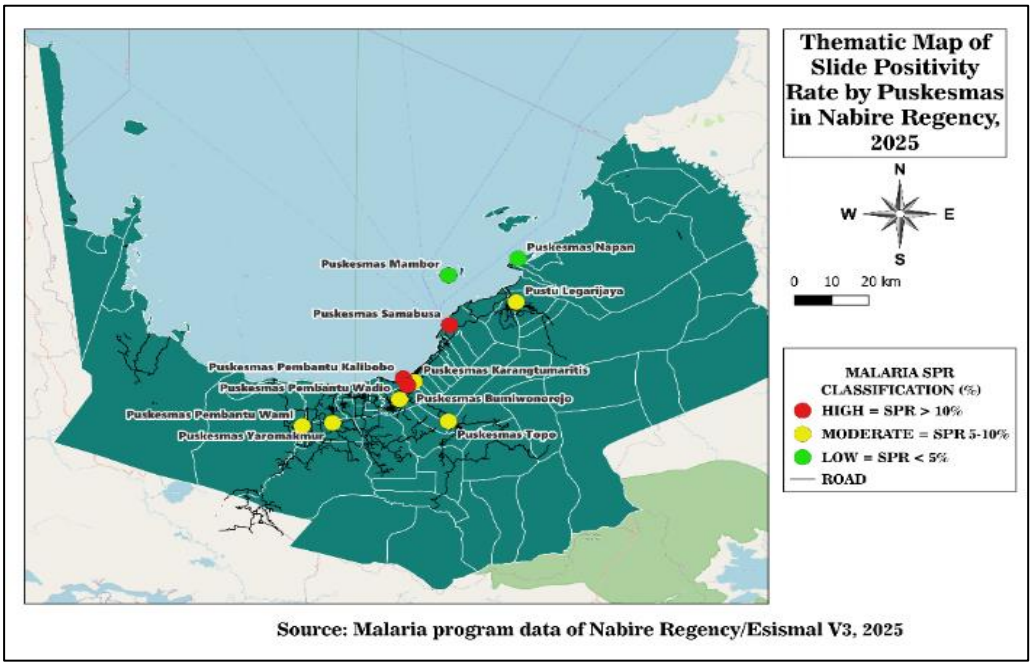


Source: Malaria program data of Nabire Regency/Esismal V3, 2025

Figure 6. Malaria Endemicity Classification Map Based on API in Nabire Regency in 2025

Figure 6 illustrates the spatial distribution of SPR in Nabire Regency in 2025. The highest SPR values were recorded in Siriwo, Samabusa, and Kalibobo, indicating a higher proportion of malaria-positive cases among examined individuals. These findings suggest the presence of localized transmission hotspots and support the need for targeted malaria control efforts.



Source: Malaria program data of Nabire Regency/Esismal V3, 2025

Figure 7. Thematic Map of Slide Positivity Rate by Puskesmas in Nabire Regency in 2025

Figure 7 illustrates the spatial distribution of the Slide Positivity Rate (SPR) across Puskesmas service areas in Nabire Regency in 2025. The highest SPR values were recorded in Siriwo (23%), Samabusa (17%), and Kalibobo (15%), indicating localized malaria transmission hotspots. To translate these spatial patterns into operational decision-support information, a multi-criteria priority scoring system integrating positive cases, API, SPR, and village-level case concentration was developed. The resulting MSPI classified Samabusa and Legari as very high-priority areas, while several other Puskesmas service areas were categorized as high, medium, or low priority according to their cumulative risk scores.

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Table 8. Scoring Results for Malaria Control Priority Areas in Nabire Regency in 2025

No.	Puskesmas	Positive Cases	Case Score	API	API Score	SPR (%)	SPR Score	Vill. Conc. Score	Total	Priority
1	Samabusa	704	3	77	3	17	3	3	12	Very high
2	Legari	410	3	76	3	7	2	3	11	Very high
3	Yaro	313	3	67	3	8	2	1	9	High
4	Wami	214	2	139	3	5	2	3	10	High
5	SP3 Topo Jaya	201	2	100	3	9	2	2	9	High
6	Kalibobo	248	2	20	2	15	3	3	10	High
7	Sanoba	206	2	29	2	11	3	3	10	High
8	SP 1 Kalibumi	353	3	30	2	6	2	3	10	High
9	Topo	110	2	62	3	8	2	1	8	Medium
10	Siriwo	58	1	54	3	23	3	1	8	Medium
11	Mambor	76	1	89	3	3	1	1	6	Medium
12	Wapoga	30	1	60	3	5	2	1	7	Medium
13	Karadiri	152	2	31	2	5	2	1	7	Medium
14	SP3 Wadio	61	1	18	2	10	2	2	7	Medium
15	Napan	46	1	31	2	3	1	1	5	Low
16	Yeretuar	27	1	43	2	1	1	1	5	Low
17	Bawei	20	1	42	2	1	1	1	5	Low
18	Maniwo	16	1	36	2	2	1	1	5	Low

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b)

Table 8 presents the results of the Malaria Spatial Priority Index (MSPI) scoring across Puskesmas service areas in Nabire Regency. The analysis identified Samabusa and Legari as very high-priority areas, with total scores of 12 and 11, respectively. Several areas, including Wami, Kalibobo, Sanoba, SP 1 Kalibumi, Yaro, and SP3 Topo Jaya, were classified as high priority due to their elevated malaria burden and epidemiological risk indicators. These findings demonstrate that malaria risk was unevenly distributed across the regency and highlight the importance of targeted interventions based on multiple epidemiological criteria rather than a single indicator.

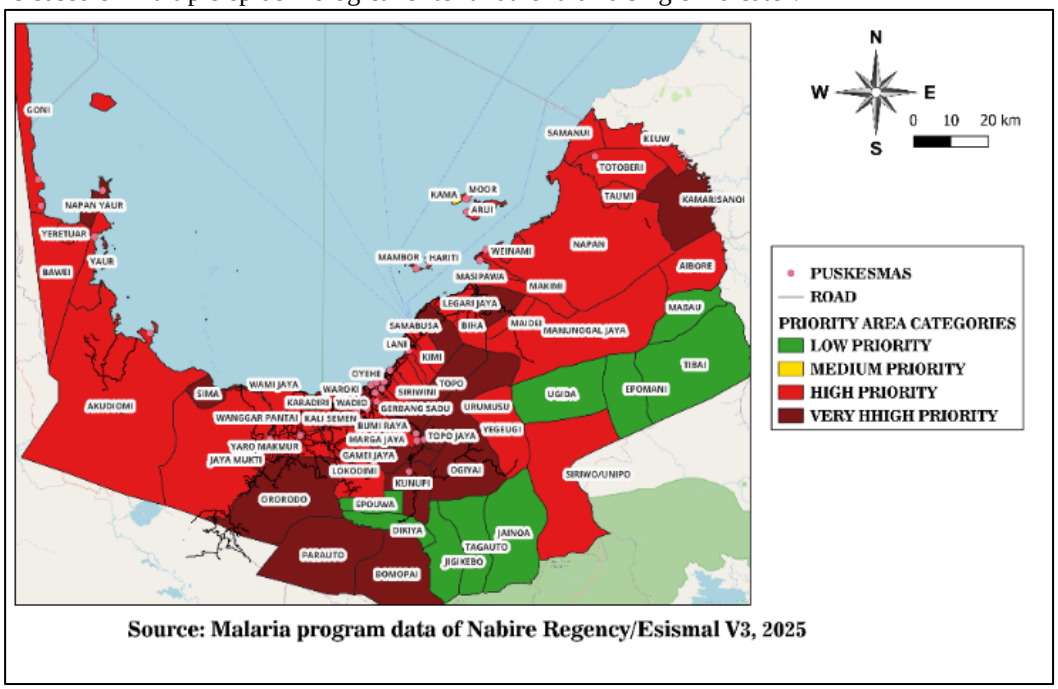

Figure 8. Map of Malaria Control Priority Areas in Nabire Regency in 2025

Complementing the Puskesmas-level assessment, village and sub-district spatial analysis identified highly localized case concentrations. Kalibobo village contributed the highest absolute number of infections with 826 cases, followed by Wami Jaya (432), Samabusa (394), Sanoba (268), and Air Mandidi (247). These locations represented the core transmission hotspots at the community level.

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Table 9. Fifteen Village/Sub-District Areas Contributing the Highest Malaria Cases in 2025

No.	Village/Sub-District	Puskesmas Area	Total Cases
1	Kalibobo	Kalibobo	826
2	Wami Jaya	Wami	432
3	Samabusa	Samabusa	394
4	Sanoba	Sanoba	268
5	Air Mandidi	Samabusa	247
6	Waroki	SP 1 Kalibumi	183
7	Nabarua	Nabarua	158
8	Bumiwonorejo	Bumi Wonorejo	147
9	Nifasi	Legari	145
10	Karang Tumaritis	Karang Tumaritis	109
11	Wadio	SP3 Wadio	100
12	Karang Mulia	Karang Mulia	99
13	Bumiraya	SP 1 Kalibumi	88
14	Biha	Legari	80
15	Argomulyo	SP3 Topo Jaya	80

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b)

Table 9 and Figure 8 illustrate the spatial concentration of malaria cases at the village and sub-district levels in 2025. Kalibobo contributed the highest number of cases (826), followed by Wami Jaya (432) and Samabusa (394). The distribution indicates that malaria transmission was concentrated in a limited number of communities rather than being uniformly distributed across Nabire Regency. These areas represent localized transmission hotspots that require strengthened surveillance, active case detection, vector control, and community-based intervention strategies.

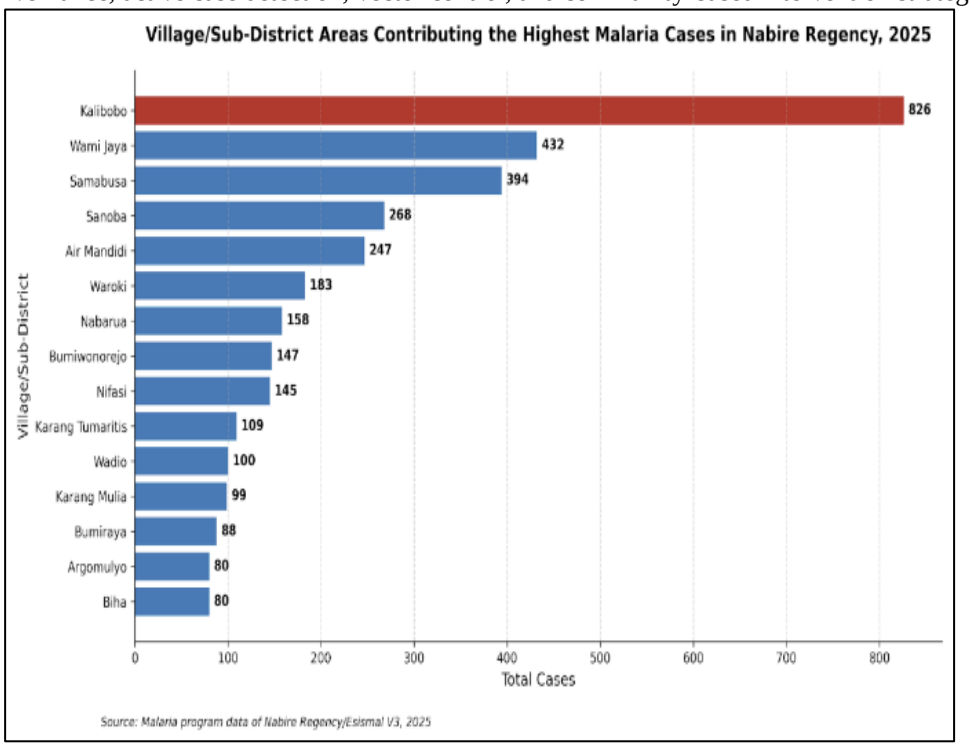

Figure 9. Village/Sub-District Areas Contributing the Highest Malaria Cases in 2025

Furthermore, the evaluation of active case detection by malaria cadres highlighted severe disparities in community surveillance coverage. Puskesmas Kwatisore and Moor achieved cadre examination percentages exceeding 90% without detecting any positive cases. In stark contrast, Sanoba and Kalibobo recorded the lowest cadre coverage (22% and 21%, respectively) despite Sanoba registering a high cadre positivity rate of 7%.

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Table 10. Malaria Examination Achievements by Cadres in Selected Puskesmas Areas in 2025

No	Area	Total Examinations	Home Visit Examinations	Cadre Examination Percentage (%)	Positive from Cadre Examination (%)
1	Kwatisore	903	829	92	0
2	Moor	2,759	2,519	91	0
3	SP3 Topo Jaya	2,265	1,907	84	5
4	Yeretuar	2,054	1,708	83	0
5	Manunggal Jaya	2,717	2,195	81	1
6	SP3 Wadio	621	486	78	0
7	Nabarua	2,647	2,016	76	0
8	Karang Mulia	4,894	3,725	76	0
9	Legari	5,592	3,883	69	1
10	Yaro	3,909	2,446	63	1
11	Samabusa	4,994	2,531	51	5
12	Sanoba	1,923	426	22	7
13	Kalibobo	2,195	459	21	0

Source: (Dinas Kesehatan Kabupaten Nabire, 2025b)

DISCUSSION

The simultaneous increase in positive cases, API, SPR, and mortality in 2025 indicates a significant worsening of the malaria situation. This temporal pattern suggests that the escalation in malaria burden was not solely an artifact of expanded examination coverage, but rather a reflection of intensified transmission dynamics and elevated population risk. These temporal dynamics align with previous longitudinal studies in Indonesia, which suggest that sudden incidence spikes in endemic regions are frequently driven by localized transmission bottlenecks and operational surveillance gaps rather than uniformly distributed population risks (Aisyah dkk., 2024; Djaafara dkk., 2025; Ridha dkk., 2022).

This spatial concentration of the malaria burden in specific Puskesmas service areas demonstrates that administrative boundaries do not uniformly dictate disease risk. Similar spatial clustering patterns have been reported in Papua and other endemic regions of Indonesia, indicating that malaria transmission heavily clusters geographically due to complex interactions between local demographics, health-service accessibility, and unmeasured environmental determinants (Fadilah dkk., 2022; Herdianti and Munadi, 2025; Lusiyana, 2024).

The emergence of Samabusa and Kalibobo as the primary spatial hotspots necessitates a critical epidemiological examination. Geographically, Samabusa operates as the primary seaport of Nabire Regency, characterized by high population mobility, extensive coastal socio-economic activities, and a constant influx of transient maritime workers. This finding aligns with previous studies indicating that coastal geography, coupled with high human mobility, significantly exacerbates localized malaria transmission risks (Hidayati dkk., 2023; Isworo dkk., 2023). Conversely, Kalibobo represents a densely populated urban and peri-urban coastal interface. The disproportionately high case incidence in Kalibobo is likely driven by dense housing conditions, inadequate environmental drainage, and proximity to stagnant water bodies that serve as ideal breeding habitats for Anopheles vectors (Lusiyana, 2024; Madayanti dkk., 2022). These distinct localized drivers demonstrate that the implementation of the MSPI model accurately captures underlying ecological and demographic vulnerabilities beyond mere numerical incidence.

The priority scoring approach confirms that malaria control prioritization should not rely on a single epidemiological indicator. High-priority areas displayed different epidemiological characteristics: Wami and SP3 Topo Jaya recorded the highest API values, Kalibobo and Sanoba showed higher SPR values, and Yaro and SP 1 Kalibumi reported relatively high absolute case numbers. By synthesizing multiple indicators, the priority scoring framework deployed in this study provides a significantly more comprehensive and robust foundation for risk stratification than single-metric evaluations (Cissoko dkk., 2025; Stresman dkk., 2025).

These findings emphasize that relying exclusively on passive surveillance is insufficient. From a health informatics perspective, GIS played a critical role in transforming routine surveillance data into operational spatial intelligence. The thematic mapping of priority areas facilitates the immediate visual identification of high-risk zones, confirming the value of GIS-based spatial decision support systems in optimizing the allocation of scarce public health resources (Fahmi dkk., 2022; Haisoufi & Bouaiti, 2024; Ramírez Montalván dkk., 2025; Yadav & Sharma, 2022). The practical implications of these findings are profound for local health authorities. The severe lack of community-based cadre examinations in heavily burdened villages such as Sanoba and Kalibobo demands immediate corrective action. Health policies must urgently prioritize the strengthening of active case detection, cadre capacity, and village-level intervention strategies specifically targeted within these mapped hotspot areas to dismantle the localized chains of transmission.

Despite its contributions, this study acknowledges several methodological limitations. The spatial-temporal analysis relied entirely on secondary routine surveillance data, which inherently poses potential variations in reporting

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completeness and diagnostic accuracy (Fransisca dkk., 2025). Geographically, the spatial assessment was restricted to aggregate Puskesmas and village-level administrative units, lacking the granular precision of individual-level coordinate data. Furthermore, the priority scoring model was constructed strictly using epidemiological indicators, intentionally excluding highly influential environmental and ecological predictors such as rainfall, temperature, humidity, land cover, population density, and vector breeding sites (Ashar, Lauchan, dkk., 2025; Ashar, Safira, dkk., 2025; Hidayati dkk., 2023; Isworo dkk., 2023; Lusiyana, 2024; Madayanti dkk., 2022; Sunarsih dkk., 2025; Tulak dkk., 2025). Finally, while the GIS-based deterministic scoring provides immediate practical utility for local health authorities, it lacks the inferential predictive power of advanced stochastic spatial statistical modeling, which future research should actively seek to incorporate.

CONCLUSION

This study demonstrates the effectiveness of Geographic Information System (GIS) for spatial-temporal malaria analysis and priority area identification in Nabire Regency. The findings revealed a substantial increase in malaria burden in 2025, indicated by higher positive cases, API, SPR, and malaria-related deaths compared with 2024. Spatial analysis showed that malaria transmission was unevenly distributed and concentrated within specific Puskesmas service areas and villages/sub-districts.

By integrating epidemiological indicators, village-level case concentration, and GIS-based spatial analysis, the proposed Malaria Spatial Priority Index (MSPI) successfully identified priority intervention areas. Samabusa and Legari were classified as very high-priority areas, while Kalibobo, Wami Jaya, Samabusa, Sanoba, and Air Mandidi emerged as the major transmission hotspots at the village level. These findings confirm that malaria control prioritization should be based on multiple epidemiological and spatial indicators rather than a single measure of disease burden.

The primary contribution of this study is the development of the MSPI framework, which transforms routine malaria surveillance data into operational spatial intelligence for evidence-based intervention planning and resource allocation. The framework provides a practical decision-support tool that can be readily implemented by local health authorities in highly endemic settings.

This study relied on routine surveillance data and employed an equal-weighting approach for priority scoring. Future studies should enhance the MSPI framework by incorporating environmental and climatic variables, applying spatial statistical techniques such as Moran's I and Getis-Ord Gi*, and exploring expert-based weighting methods to improve malaria risk prediction and intervention targeting.

RECOMMENDATIONS

Malaria control programs in Nabire Regency should prioritize interventions in very high- and high-priority areas identified through the MSPI framework. Strengthening active case detection, community-based surveillance, malaria cadre capacity, and targeted vector control in hotspot villages is recommended to reduce localized transmission. Furthermore, the routine integration of GIS into malaria surveillance systems should be encouraged to support evidence-based planning, efficient resource allocation, and timely public health responses.

REFERENCES

Aisyah, D. N., Sitompul, D., Diva, H., Tirmizi, S. N., Hakim, L., Surya, A., Puspadewi, R. T., Prameswari, H. D., Adisasmito, W., & Manikam, L. (2024). The Changing Incidence of Malaria in Indonesia: A 9-Year Analysis of Surveillance Data. *Advances in Public Health*, *2024*(1), 2703477. https://doi.org/10.1155/ADPH/2703477

Ashar, Y. K., Lauchan, A. M., & Safira, P. (2025). Analysis of Environmental Risk Factors Associated with Malaria Incidence in Papua, Indonesia. *Jurnal Kesehatan Lingkungan*, *17*(3), 287–293. https://doi.org/10.20473/jkl.v17i3.2025.287-293

Ashar, Y. K., Safira, P., & Lauchan, A. M. (2025). Association Between Climatic Factors and Malaria Incidence in Papua, Indonesia. *Gema Lingkungan Kesehatan*, *23*(3), 438–444. https://doi.org/10.14710/glk.2025.23.3.438-444

Cissoko, M., Magassa, M., Cissé, I. A., Coulibaly, S., Samaké, D. S., Sanogo, V., Koné, M., Thiam, S., Ballo, T., Diarra, S., Fomba, S., Koné, A., Gaudart, J., & Sagara, I. (2025). Geo-epidemiological risk stratification to select malaria interventions, case of Mali. *PLOS Global Public Health*, *5*(11), e0004796. https://doi.org/10.1371/journal.pgph.0004796

Damanik, A. R., Zer, P. P. P. A. N. W. F. I. R. H., Zulpani, R., & Batubara, E. (2025). Implementation of Machine Learning Virtual Medical Assistant Using NLP for Stunting and Healthcare Efficiency in Simalungun. *Brilliance: Research of Artificial Intelligence*, *5*(2), 719–726. https://jurnal.itscience.org/index.php/brilliance

Dinas Kesehatan Kabupaten Nabire. (2025a). *Capaian Program Kabupaten Nabire Malaria Tahun 2025*. Dinas Kesehatan Kabupaten Nabire.

Dinas Kesehatan Kabupaten Nabire. (2025b). *Data Esismal V3: Tren Kasus, Pemeriksaan, API, ABER, SPR, dan Kematian Malaria Kabupaten Nabire Tahun 2018–2025. Nabire: Dinas Kesehatan Kabupaten Nabire, 2025.*

Djaafara, B. A., Sherrard-Smith, E., Churcher, T. S., Fajariyani, S. B., Prameswari, H. D., Herdiana, H., Puspadewi, R.

E-ISSN : 2807-9035
Volume 6, **Number** 2, May 2026
https://doi.org/10.47709/brilliance.v6i2.8775

T., Lestari, K. D., Elyazar, I. R. F., & Walker, P. G. T. (2025). Spatiotemporal heterogeneity in malaria transmission across Indonesia: analysis of routine surveillance data 2010--2019. *BMC Medicine*, *23*(1), 136. https://doi.org/10.1186/s12916-025-03353-8

Fadilah, I., Djaafara, B. A., Lestari, K. D., Fajariyani, S. B., Sunandar, E., Makamur, B. G., Wopari, B., Mabui, S., Ekawati, L. L., Sagara, R., & others. (2022). Quantifying spatial heterogeneity of malaria in the endemic Papua region of Indonesia: Analysis of epidemiological surveillance data. *The Lancet Regional Health - Southeast Asia*, *5*, 100051. https://doi.org/10.1016/j.lansea.2022.100051

Fahmi, F., Pasaribu, A. P., Theodora, M., & Wangdi, K. (2022). Spatial analysis to evaluate risk of malaria in Northern Sumatera, Indonesia. *Malaria Journal*, *21*(1), 241. https://doi.org/10.1186/s12936-022-04264-5

Fransisca, L., Burdam, F. H., Kenangalem, E., Rahmalia, A., Ubra, R. R., van den Boogaard, C. H. A., Ley, B., & Douglas, N. M. (2025). Enhanced data quality to improve malaria surveillance in Papua, Indonesia. *Malaria Journal*, *24*(1), 177. https://doi.org/10.1186/s12936-025-05298-z

Haisoufi, D., & Bouaiti, E. A. (2024). State of the art on the contributions and use of geographic information systems (gis) in epidemiology in morocco. *Open Public Health Journal*, *17*(1), e18749445312011. https://doi.org/10.2174/0250680717666240215112011

Hasifah, H., & Rinenggantyas, N. (2026). Investigasi dan Pemetaan Resistensi Nyamuk Anopheles di Wilayah Endemik di Kabupaten Sumbawa. *Jurnal Kesehatan Lingkungan Indonesia*, *25*(1), 28–38. https://doi.org/10.14710/jkli.25.1.28-38

Herdianti and Munadi, M. C. H. H. and L. I. A. and F. N. A. and H. (2025). Spatiotemporal Clustering of Malaria in South Sumatra, Indonesia, Based on Surveillance Data, 2018--2022. *Advances in Public Health*, *2025*, 5234228. https://doi.org/10.1155/2025/5234228

Hidayati, F., Raharjo, M., Martini, M., Wahyuningsih, N. E., & Setiani, O. (2023). Hubungan Kualitas Lingkungan dengan Kejadian Malaria (Wilayah Endemis Malaria, Lingkup Kerja Puskesmas Kaligesing, Kabupaten Purworejo Tahun 2022). *Jurnal Kesehatan Lingkungan Indonesia*, *22*(1), 21–27. https://doi.org/10.14710/jkli.22.1.21-27

Isworo, Y., Hadi, S. P., & Setiyani, O. (2023). Faktor-faktor kerentanan sosial dan lingkungan yang berhubungan dengan kejadian malaria di Kabupaten Kulon Progo. *Jurnal Ilmu Lingkungan*, *21*(3), 725–734. https://doi.org/10.14710/jil.21.3.725-734

Kemenkes RI. (2022). *Peraturan Menteri Kesehatan Republik Indonesia Nomor 22 Tahun 2022 tentang Penanggulangan Malaria*. Kementerian Kesehatan Republik Indonesia. https://peraturan.bpk.go.id/Details/234208/permenkes-no-22-tahun-2022

Legendre, E., Lehot, L., Dieng, S., Rebaudet, S., Thu, A. M., Rae, J. D., Delmas, G., Girond, F., Herbreteau, V., Nosten, F., Landier, J., & Gaudart, J. (2023). Malaria temporal dynamic clustering for surveillance and intervention planning. *Epidemics*, *43*, 100682. https://doi.org/10.1016/j.epidem.2023.100682

Lusiyana, N. (2024). Prevalens dan Faktor Risiko Malaria di Distrik Iwaka, Mimika, Papua. *Jurnal Kedokteran dan Kesehatan*, *20*(1), 45–56. https://doi.org/10.24853/jkk.20.1.45-56

Madayanti, S., Raharjo, M., & Purwanto, H. (2022). Faktor Risiko Yang Mempengaruhi Kejadian Malaria di Wilayah Distrik Jayapura Selatan Kota Jayapura. *Jurnal Kesehatan Lingkungan Indonesia*, *21*(3), 358–365. https://doi.org/10.14710/jkli.21.3.358-365

Muhandisin, A., & Azhar, Y. (2022). Malaria blood cell image classification using transfer learning with fine-tune resnet50 and data augmentation. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, *6*(5), 891–897. https://doi.org/10.29207/resti.v6i5.4431

Mwangungulu, S. P., Dorothea, D., Ngereja, Z. R., & Kaindoa, E. W. (2023). Geospatial based model for malaria risk prediction in Kilombero valley, South-eastern, Tanzania. *PLoS ONE*, *18*(10), e0293201. https://doi.org/10.1371/journal.pone.0293201

Ngadino, Winarko, Nurmayanti, D., Marlik, Wardoyo, S., Nurhayati, S., & Wuryaningtyas, D. (2024). Spatial analysis of malaria cases and Anopheles species in East Java region, Indonesia. *Tropical Medicine and Health*, *52*(1), 91. https://doi.org/10.1186/s41182-024-00652-3

Nikolova, S., & Aleksandrova, T. (2025). Geospatial Insights into Healthcare Accessibility in Europe: A Scoping Review of GIS Applications. *Healthcare*, *13*(24), 2865. https://doi.org/10.3390/healthcare13242865

Ramírez Montalván, W., Manzano Gallardo, I., Defaz Toapanta, V., Espinosa Gallardo, E., & Garcés Guayta, L. (2025). Reproducible GIS-Based Evidence for Public Health and Urban Security: A Systematic Mapping and Review. *ISPRS International Journal of Geo-Information*, *15*(1), 4. https://doi.org/10.3390/ijgi15010004

Ridha, M. R., Indriyati, L., Juhairiyah, J., & Kusumaningtyas, H. (2022). Malaria incidence trends and their association with climatic variables in East Kalimantan, Indonesia, 2014-2020. *Jurnal Epidemiologi dan Penyakit Bersumber Binatang*, *4*(1), 33–42. https://doi.org/10.22435/jepbb.v4i1.6247

Sahputra, I., Ilhadi, V., Pratama, A., Syukriah, & Arifa, T. M. (2025). Decision Support System for Potential Stock Selection Recommendations Using AHP and Profile Matching Methods. *Brilliance: Research of Artificial Intelligence*, *5*(1). https://jurnal.itscience.org/index.php/brilliance

E-ISSN : 2807-9035
Volume 6, **Number** 2, May 2026
https://doi.org/10.47709/brilliance.v6i2.8775

Setyawan, D., Wardoyo, R., Wibowo, M. E., & Murhandarwati, E. E. H. (2022). Classification of plasmodium falciparum based on textural and morphological features. *International Journal of Electrical and Computer Engineering*, *12*(5), 5036–5048. https://doi.org/10.11591/ijece.v12i5.pp5036-5048

Stresman, G., Nelli, L., Wu, L., Byrne, I., Surendra, H., Fernandez-Camacho, B., Ruiz-Cabrejos, J., Bartolini Arana, L., Macedo Gonçalves, A. A. L., Rocha Monteiro, D. D. S., Desir, L., Ureña, K., Tejada Beato, M. de J., Dumont, E., Hill, M., Grignard, L., Elechosa, S., Bunagan, R., Thang, N. X., … Drakeley, C. (2025). Evidence-based decision making for malaria elimination applying the Freedom From Infection statistical framework in five malaria eliminating countries: an observational study. *The Lancet Global Health*, *13*(9), e1591--e1604. https://doi.org/10.1016/S2214-109X(25)00241-1

Sunarsih, E., Mutahar, R., & Fauziah, N. (2025). Analisis Spasial Dinamika Penularan Malaria di Wilayah Dataran Tinggi Kabupaten Muara Enim. *Jurnal Kesehatan Lingkungan Indonesia*, *24*(2), 194–199. https://doi.org/10.14710/jkli.24.2.194-199

Syahrani, L., Dwiranti, A., Asih, P. B. S., Rozi, I. E., Permana, D. H., Bowolaksono, A., & Syafruddin. (2025). Susceptibility of the Punctulatus group (Diptera: Culicidae) to insecticide carbamate in Papua, Indonesia. *Biodiversitas Journal of Biological Diversity*, *26*(3), 1376–1383. https://doi.org/10.13057/biodiv/d260309

Tulak, N., Kareth, Z. V., & Tapatkeding, H. W. (2025). Hubungan antara kerapatan indeks vegetasi NDVI dan curah hujan dengan sebaran habitat akuatik nyamuk Anopheles sp. di Distrik Muara Tami Kota Jayapura. *Jurnal Ilmu Lingkungan*, *23*(3), 776–783. https://doi.org/10.14710/jil.23.3.776-783

WHO. (2024). *WHO Malaria Policy Advisory Group (MPAG) meeting report, 4, 5 and 7 March 2024*. World Health Organization. https://www.who.int/publications/i/item/9789240094000

Yadav, C. P., & Sharma, A. (2022). National Institute of Malaria Research-Malaria Dashboard (NIMR-MDB): A digital platform for analysis and visualization of epidemiological data. *The Lancet Regional Health - Southeast Asia*, *5*, 100043. https://doi.org/10.1016/j.lansea.2022.100043

Zubaedah, R., & Prasetyo, H. (2022). Decision Support System for High School Entrance Selection. *Brilliance: Research of Artificial Intelligence*, *2*(2), 71–74. https://doi.org/10.47709/brilliance.v2i2.1566