



SPATIAL MODELING OF MALARIA INCIDENCE BASED ON GIS: A SYSTEMATIC REVIEW (2016–2025)

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ABSTRACT

Malaria remains a public health challenge in Indonesia, particularly in eastern regions such as Sorong City, which exhibits geographically heterogeneous transmission patterns. Geographic Information Systems (GIS)-based spatial modeling is increasingly used to understand malaria risk distribution and support elimination efforts. This study aims to synthesize scientific evidence on methods, determinants, and key findings of spatial modeling

studies on malaria incidence using GIS. The method employed is a systematic literature review of original research articles from Scopus, PubMed, OpenAlex, and Google Scholar published between 2016–2025 and accredited by Scopus (Q1–Q4) and/or SINTA (1–2). Following a rigorous screening process, ten eligible articles ($n = 10$) were selected and included in the final synthesis. The results indicate that dominant methods include spatial regression, spatial–spatiotemporal cluster analysis, GIS-based MCDA, and descriptive mapping, with key determinants comprising climatic factors, elevation, proximity to water sources, vector density, population mobility, and access to healthcare services. In conclusion, GIS-based spatial modeling is effective for identifying malaria hotspots and supporting more targeted intervention planning. It is recommended that GIS be integrated into malaria surveillance in Sorong City and further developed using spatiotemporal approaches to strengthen evidence-based policy-making.

INTRODUCTION

Malaria remains a significant global health threat, especially in tropical and subtropical countries. According to the World Health Organization (WHO), there were an

estimated 263 million cases of malaria and 597,000 deaths worldwide in 2023, an increase of approximately 11 million cases compared to 2022 (WHO, 2024). The African region bears the heaviest burden, accounting for 94% of

global cases and 95% of malaria-related deaths, with the majority of victims being children under five years of age living in areas with limited access to healthcare services (WHO, 2024). Despite a 50% reduction in malaria mortality rates since 2000, from 28.5 to 13.7 deaths per 100,000 at-risk population, the challenge of global malaria elimination remains far from achieved (WHO, 2024). This situation requires innovative and evidence-based approaches to improve the effectiveness of malaria control and elimination programs in various endemic regions.

Indonesia faces serious challenges in its efforts to eliminate malaria nationwide by 2030. Data shows significant fluctuations in the malaria burden in Indonesia, with 464,764 cases in 2010, decreasing to 304,607 cases in 2021, but rising sharply to 418,546 cases in 2023 (APLMA, 2024). Although 85% of Indonesia's population now lives in malaria-free areas and 398 districts/cities (77%) have received malaria elimination certification as of June 2024, more than 400,000 cases of malaria are still reported annually, mainly from the Papua region (APLMA, 2024). In the Southeast Asia region, Indonesia accounts for 9% of all malaria cases, with incidence continuing to rise in eastern Indonesia (Aisyah et al., 2024). The sharp geographical disparity between western Indonesia, which has achieved elimination, and eastern Indonesia, which remains highly endemic, highlights the need for control strategies tailored to the local characteristics of each region.

Papua and West Papua are the epicenter of Indonesia's malaria burden, accounting for more than 90% of national malaria cases despite comprising only 1.5% of Indonesia's total population (Wahono, 2025). Data from 2024 shows that Indonesia reported more than 543,000 malaria cases, with 95% concentrated in the provinces of Papua and East Nusa Tenggara (Wahono, 2025). In Papua, 14 districts/cities with very high transmission rates (API > 250 per 1,000 population) are the main focus of the malaria elimination acceleration program (APLMA, 2024). The spatial heterogeneity of malaria transmission in Papua is very high, with *Plasmodium falciparum* parasite prevalence varying from 0% to more than 40% in various districts (Rozi et al., 2024). Geographical conditions such as lowlands with year-round rainfall, extreme poverty, limited health infrastructure, difficult terrain, and challenges in inter-district coordination are factors that complicate malaria elimination efforts in this region (Wahono, 2025).

The city of Sorong, as one of the regions in Southwest Papua, faces the challenge of high malaria endemicity. Epidemiological data shows a fluctuating trend in malaria cases in Sorong City, with 766 positive cases in 2021, a drastic increase to 1,749 cases in 2022 (an increase of 128.3%), and peaking in 2023 with 3,831 cases (Kemenkes, 2023). Despite a decline to 2,818 cases in 2025 (a 28.2% decrease from 2024), malaria still ranks among the top ten diseases

in Sorong City health centers and remains a cause of death (Kemenkes, 2023). The districts with the highest number of cases were identified as Maladum Mes, West Sorong, Sorong Islands, and Manoi, with data from January to April 2025 showing that there were still quite a number of cases in these areas (Malaria Perdhaki, 2025). The malaria elimination target for Sorong City is set for 2029, requiring accelerated evidence-based intervention efforts and a deep understanding of the spatial distribution of this disease (Kemenkes, 2023).

Geographic Information Systems (GIS) have proven to be a powerful tool in the surveillance and modeling of infectious diseases, including malaria. Geospatial technology enables the integration of geographic, ecological, and epidemiological data to identify transmission hotspots, map high-risk areas, and guide the allocation of disease control resources (Saran et al., 2020). In the context of the COVID-19 pandemic, the use of GIS has shown a crucial role in developing spatial data infrastructure for surveillance, integrating mobility data into infectious disease forecasting, and investigating geographic vulnerability and health disparities (Franch-Pardo et al., 2020). Advances in GIS technology enable the analysis of disease hotspots and coldspots, spatial scan statistics for cluster identification, and geographically weighted regression (GWR) modeling that can explain spatial variations in disease incidence by considering

local factors (Mollalo et al., 2020). The Multi-Criteria Decision Analysis (MCDA) approach integrated with GIS also enables the creation of comprehensive risk models by combining satellite remote sensing data, climate variables, environmental characteristics, and malaria surveillance data (Zhao et al., 2020).

Although spatial modeling of malaria using GIS has been widely applied in various countries, there is still a knowledge gap regarding the synthesis of the latest scientific evidence on methods, analytical approaches, and key findings from spatial malaria studies. Systematic literature reviews are a very important methodological approach in health research because they use systematic methods to identify, evaluate, and summarize all findings from individual studies relevant to a health issue, making the available scientific evidence more accessible to decision makers (Saran et al., 2020). Unlike narrative reviews, which are written narratively by experts after reviewing the literature in a non-systematic manner and are prone to bias, systematic reviews combine comprehensive searches with critical assessments to answer clearly formulated research questions in a systematic, transparent, and reproducible manner (Moosapour et al., 2021). This approach not only synthesizes existing evidence but also identifies research priorities, answers questions that may not be answered by individual studies, and identifies gaps that need to be addressed in future primary research (Shehata & D'Souza, 2025).

Therefore, a systematic literature review on “Spatial Modeling of Malaria Incidence Using GIS (Geographic Information System)” is very important to conduct. The purpose of this study is to synthesize the latest scientific evidence from studies that have used spatial modeling and GIS approaches in the analysis of malaria cases, identify the most effective spatial analysis methods, map existing research gaps, and provide evidence-based recommendations for strengthening malaria control programs, especially in highly endemic areas such as Sorong City. This systematic review is expected to provide a strong scientific basis for health policymakers and researchers in designing more targeted, efficient, and sustainable malaria control interventions through the use of geospatial technology.

METHODS

The research method in this study uses a systematic literature review (SLR) approach to systematically identify and synthesize scientific evidence related to spatial modeling of malaria incidence using Geographic Information Systems (GIS). The literature search was conducted in four main databases: Scopus, PubMed, OpenAlex, and Google Scholar, using a combination of the keywords "malaria", "spatial analysis", and "GIS". Inclusion criteria cover original research articles discussing GIS-based spatial analysis or modeling of malaria, published between 2016–2025, and indexed and accredited in

Scopus (Q1–Q4) and/or SINTA rankings 1–2. Exclusion criteria include review articles, reports, proceedings, editorials, and non-research publications. Following a multi-stage screening process, ten eligible studies were selected, and their methodological quality and risk of bias were independently evaluated by two reviewers using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Analytical Cross-Sectional Studies, with only moderate-to-high quality studies retained to ensure credibility. Finally, data from the qualified studies were extracted and analyzed using a qualitative narrative synthesis structured around the spatial methods applied, environmental and sociodemographic determinants, and the practical implications of risk mapping for malaria control. Articles that met the criteria were then subjected to data extraction and descriptive analysis to identify spatial analysis methods, malaria determinant variables, and their implications for malaria control.

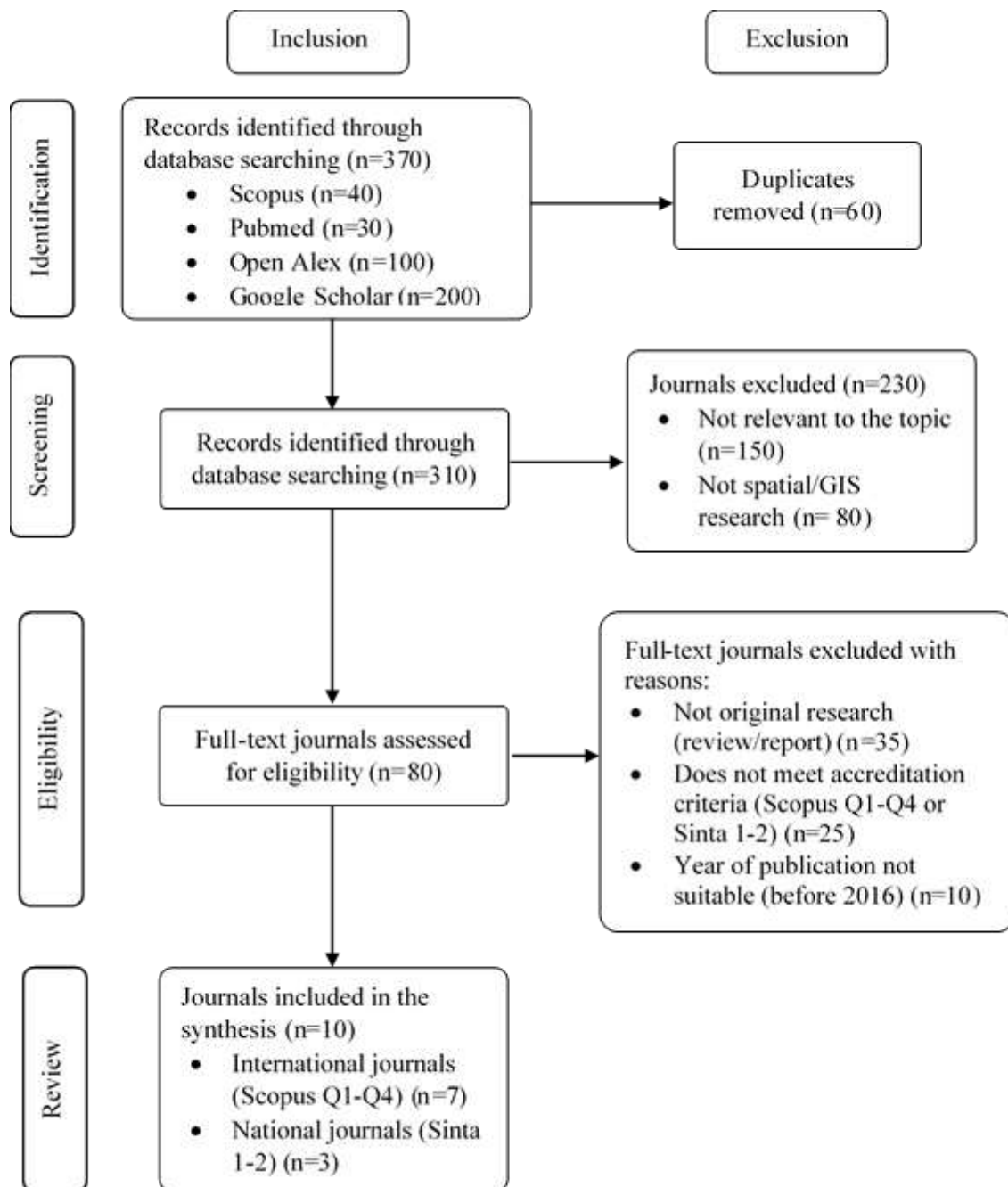


Figure 1. PRISMA Diagram

Source: Primary Data 2026

RESULTS

The results section of this systematic literature review presents the main findings from the process of searching, selecting, and synthesizing scientific articles discussing spatial modeling of malaria incidence using Geographic Information Systems (GIS). The

literature identification process across the Scopus (n=370), PubMed (n=30), OpenAlex (n=100), and Google Scholar (n=200) databases yielded 740 articles, which were then selected step-by-step based on the established inclusion and exclusion criteria. The article selection flow is presented in a PRISMA Diagram to transparently illustrate

the number of articles at each stage, from initial identification to the articles ultimately analyzed. Subsequently, the characteristics and key findings of the selected articles are presented in the form of a journal synthesis table containing information such as research title, author(s), journal, spatial analysis methods used, and main results relevant to spatial modeling of malaria. This presentation aims to provide a comprehensive overview of the variety of methodological approaches, the determinant factors analyzed, and the spatial patterns of malaria incidence found across different regional contexts, serving as a basis for further analysis and discussion.

The PRISMA Diagram in this study systematically illustrates the stages of the literature search and selection process conducted until articles meeting the inclusion criteria were obtained. The initial search across the Scopus, PubMed, OpenAlex, and Google

Scholar databases yielded a total of 330 articles related to the spatial modeling of malaria using GIS. After removing duplicates and screening based on titles and abstracts, the majority of articles were eliminated for reasons including irrelevance to the topic, not using a spatial/GIS approach, not being original research, or not meeting the Scopus (Q1–Q4) and SINTA (1–2) accreditation criteria. In the full-text eligibility review stage, the remaining articles were rigorously evaluated again to ensure alignment with the study's objectives and the 2016–2025 publication range. Consequently, 10 articles were ultimately obtained that fulfilled all inclusion criteria. These ten articles were then subjected to in-depth analysis and synthesis, as presented in the journal synthesis table, to identify spatial analysis methods, malaria determinant factors, and their implications for malaria control and elimination.

Table 1. Summary Table of Peer-Reviewed Journals

No.	Title	Authors	Journal	Methods	Result
1.	Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia	Hamzah Hasyim, Afi Nursafingi, Ubydul Haque, Doreen Montag, David A. Groneberg, Meghnath Dhimal, Ulrich Kuch & Ruth Müller	<i>Malaria Journal</i> , volume 17, article number 87 (2018)	Analysis of confirmed malaria cases in 2013 from 436 villages. Using Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR). Analyzing 6 ecological predictors of malaria cases. Exploring global patterns and spatial variability	Elevation, distance from forests, and rainfall significantly correlate with malaria cases in the global OLS model. The GWR model shows that the relationship between malaria and environmental factors varies greatly spatially across different regions of South Sumatra, indicating the importance of different environmental and geographic parameters at the global and village levels.

2.	Spatial analysis to evaluate risk of malaria in Northern Sumatera, Indonesia	Fahmi Fahmi, Ayodhia Pitaloka Pasaribu, Minerva Theodora & Kinley Wangdi	<i>Malaria Journal</i> , Volume 2 1, article number 241 (2022)	Malaria case data for 2019-2020 from the Ministry of Health's electronic database. Multivariate logistic regression for imported malaria risk factors. Multivariate zero-inflated Poisson regression model to analyze the effect of climate on indigenous malaria. Climate data from BMKG.	Of the 2,208 cases (76% indigenous, 17.8% imported), risk factors for imported malaria were age 19-30 years (AOR=3.31), 31-45 years (AOR=5.69), >45 years (AOR=5.11), military personnel (AOR=197.03), and forest/mining workers (AOR=44.16). <i>P. falciparum</i> increased by 12.1% per 1% increase in humidity and 21% per 1°C increase in maximum temperature. <i>P. vivax</i> decreased by 0.8% per 1 meter of altitude and 16.7% per 1°C increase in minimum temperature. Indigenous hotspots: Tanjung Balai and Asahan. Imported hotspots: Batu Bara, Tebing Tinggi, Serdang Bedagai, and Simalungun.
3.	Spatial analysis of malaria cases and Anopheles species in East Java region, Indonesia	Ngadino, Winarko, Demes Nurmayanti, Marlik, Slamet Wardoyo, Syarifah Nurhayati & Desya Wuryaningtyas	<i>Tropical Medicine and Health</i> , Volume 5 2, article number 91, (2024)	Observational design with a cross-sectional approach. Malaria case data from 2021 to 2023 from the Ministry of Health's malaria information system. Purposive sampling for mosquito and larva sampling in three districts (Trenggalek, Malang, Pacitan). Analysis of the spatial distribution of cases and Anopheles vectors.	The distribution of imported malaria is uneven, with hotspots in areas that have worker mobility from outside East Java. <i>An. sundaicus</i> and <i>An. maculatus</i> have the potential to be vectors, with <i>An. sundaicus</i> more common in coastal areas and <i>An. maculatus</i> in valleys and rice fields. Environmental factors (topography, temperature, humidity, rainfall) influence the variation of Anopheles species. The study emphasizes the importance of an ecosystem-based approach, improved access to health services,

					and community education to maintain malaria elimination areas.
4.	Spatial and spatio-temporal analysis of malaria in the state of Acre, western Amazon, Brazil.	Leonardo Augusto Kohara Melchior & Francisco Chiaravalloti Neto	<i>Geospatial Health</i> , Vol. 11, No. 3 (2016)	Time series ecological study of malaria cases and deaths for the period 1992-2014. Calculating the API (Annual Parasite Incidence) index based on age, gender, and parasite species. Using SaTScan for spatial and spatiotemporal cluster detection. Visualization with choropleth maps.	High-risk clusters were detected in Vale do Juruá and three low-risk clusters in Vale do Acre for both parasite species. Individuals <19 years old and women showed high incidence in Vale do Juruá, while working-age men were most affected in Vale do Acre. Malaria mortality rates declined across the state, but the case fatality rate increased only in the Rio Branco micro-region. Malaria is a focal disease in Acre with spatial and spatiotemporal patterns that vary according to age, sex, and parasite species, so control strategies must be tailored to regional characteristics.
5.	Spatial Analysis and Mapping of Malaria Risk Areas Using Geospatial Technology in the Case of Nekemte City, Western Ethiopia	Dechasa Diriba, Shankar Karuppannan, Teferi Regasa, Melion Kasahun	<i>International Journal of Health Geographics</i> , volume 23, issue 1, (2024)	Integration of environmental factors (elevation, rainfall, temperature, slope, proximity to rivers) and social factors (population density, access to healthcare, roads). Analytic Hierarchy Process (AHP) for factor weighting. Weighted Overlay Analysis to combine hazard, vulnerability, and LULC layers. Generation of final malaria risk map.	The malaria risk map identifies 18.2% of the area (10.5 km ²) as very high risk, 18.8% (10.9 km ²) as high risk, 30.4% (17.8 km ²) as moderate risk, 19.8% (11.5 km ²) as low risk, and 12.6% (7.3 km ²) as very low risk. A total of 37% (21.4 km ²) of the Nekemte region is classified as high to very high risk. This risk map provides actionable insights to guide local health strategies, optimize resource distribution, and improve intervention efficiency, as well as support future public health planning and regional malaria control initiatives.

6.	Spatial and Spatio-temporal Analysis of Malaria Cases in Zimbabwe	Isaiah Gwitira, Munashe Mukonoweshuro, Grace Mapako, Munyaradzi D. Shekede, Joconiah Chirenda & Joseph Mberikunashe	<i>Infectious Disease of Proverty</i> , Volume 9, article number 146, (2020)	Using GIS and spatial scan statistics on passive malaria data from health facilities. Global Moran's I test to examine spatial autocorrelation. Pure spatial retrospective analysis with discrete Poisson models for cluster detection. Space-time retrospective analysis for spatiotemporal cluster detection.	There is significant positive spatial autocorrelation in malaria cases. Malaria exhibits spatial heterogeneity with statistically significant spatial and space-time clusters ($P < 0.05$) in specific geographic areas. Primary clusters persisted in eastern regions during the 6-year study period. The temporal pattern of malaria reflects the seasonality of the disease, with clusters detected in certain months of the year.
7.	Malaria Risk Map Using Spatial Multi-Criteria Decision Analysis along Yunnan Border During the Pre-elimination Period	Xiaotao Zhao, Weerapong Thanapongtharm, Siam Lawawirojwong, Chun Wei, Yerong Tang, Yaowu Zhou, Xiaodong Sun, Liwang Cui, Jetsumon Sattabongkot, Jaranit Kaewkungwal	<i>The American Journal of Tropical Medicine and Hygiene</i> , Volume 103, issue 2, (2020)	Multi-Criteria Decision Analysis (MCDA) integrated with GIS. Integrating satellite remote sensing data and malaria surveillance data from 18 districts. Creating composite models and annual risk maps based on expert consensus. Study area: China-Myanmar border in Yunnan Province.	Experts identified relative weights for 9 socioeconomic and ecological factors of the disease: Forest coverage (0.041), Cropland (0.086), Water body (0.175), Elevation (0.297), Population density (0.043), Imported cases (0.258), Distance to roads (0.030), Distance to health facilities (0.033), and Urbanization (0.036). The expert-based model has good predictive capacity with a high area under the curve. The study demonstrates the use of spatial MCDA that integrates multiple environmental factors in disease risk estimation using quantitative and qualitative criteria. The MCDA risk model and map can focus elimination efforts on specific high-risk locations.

8.	Analisis Spasial Dinamika Penularan Malaria di Wilayah Dataran Tinggi Kabupaten Muara Enim	Elvi Sunarsih , Hamzah Hasyim, Imelda Gernauli Purba, Inoy Trisnaini, Amrina Rosyada, Maurend Yayank Lewinsca, Fakhriyatiningrum Fakhriyatiningrum	<i>Jurnal Kesehatan Lingkungan Indonesia</i> , Volume 24, Issue 2, (2025)	The Geographic Information System (GIS)-based survey method used secondary data on malaria cases from 2021 to 2023 from two subdistricts (Lawang Kidul and Tanjung Agung). Data was obtained from the Muara Enim District Health Office, Tanjung Enim Community Health Center, and Tanjung Agung Community Health Center.	Spatial analysis identified the distribution of malaria cases, mine pits, swamp areas, plantations, river flow areas, and vegetation (shrubs). Areas with high concentrations of malaria cases are generally located near rivers and swamps, indicating a relationship between geographical characteristics (wet and watery areas) and an increase in malaria cases. The majority of the area consists of plantations, followed by rice fields, wetlands, and shrubs that mosquitoes can use as resting places. Areas with high cases are generally in lowlands with access to water sources such as rivers and wetlands based on univariate analysis using spatial data.
9.	Analisis Spasial Karakteristik Lingkungan dan Dinamika Kepadatan Anopheles sp. Pengaruhnya terhadap Kejadian Malaria di Kecamatan Seram Barat Kabupaten Seram Bagian Barat Maluku	Efraim Watmanlusy, Mursid Raharjo, Nurjazuli Nurjazuli	<i>Jurnal Kesehatan Lingkungan Indonesia</i> , volume 18, issue 1, (2019)	An analytical cross-sectional observational study of 100 respondents using purposive sampling in West Seram Subdistrict. Data collection was conducted through interviews, observation, and mosquito capture using the human landing catch method inside and outside homes. Data analysis was performed using the chi-square test.	Of the 100 respondents, 41 tested positive for malaria. Five species of Anopheles were found: An. vagus, An. tessellatus, An. koichi, An. barbirotris, and An. farauti, but they have not been confirmed as malaria vectors based on PCR test results. Factors influencing the incidence of malaria: air temperature (p=0.022, PR=2.082), humidity (p=0.003, PR=3.421), density of Anopheles sp. (p=0.001, PR=2.853), and distance from breeding sites (p=0.000, RP=10.054).
10.	Distribusi Spasial	Henny Sesanti Budi	<i>Sebatik</i> , volume	A descriptive study with an exploratory	There were 290 malaria patients with the highest

	Penderita Malaria di Distrik Sentani Timur Kabupaten Jayapura	Hastuty & Denik Wahyu Setyowati	25, issue 1, (2021)	design using an observational and survey approach with a Geographic Information System (GIS). The population consisted of all malaria patients in Nolakla Village recorded in the outpatient register of the Harapan Community Health Center in East Sentani District for the period January-March 2019.	incidence in the 15-64 age group (52.1%), males (53%), residents of RW 3 (37.9%), and March (40.4%). The spatial distribution map for February-March showed an even distribution across all RWs with a total of 98 patients. RW 3 had the most cases (37 individuals). The homes of malaria patients were located near forests and wetlands with puddles and pools of water that could serve as breeding sites for Anopheles sp. larvae.
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Source: Secondary Data by Journal/Article Publisher2026

DISCUSSION

This systematic literature review process began with a comprehensive search of four major databases, namely Scopus, PubMed, OpenAlex, and Google Scholar, which yielded 330 journals on spatial modeling of malaria using Geographic Information Systems (GIS). Through a rigorous PRISMA selection process involving identification, screening, eligibility, and inclusion, 320 journals were eliminated for various reasons, such as duplication, irrelevance to the topic, not being original research (reviews or reports), not using spatial/GIS methods, and not meeting the established accreditation criteria of Scopus Q1-Q4 or Sinta 1-2. After a systematic and transparent selection process, 10 journals finally met the established inclusion criteria, consisting of 7 international journals indexed in Scopus and 3 nationally accredited Sinta

journals, which were then analyzed in depth to identify spatial analysis methods, malaria determinants, and implications for malaria control and elimination programs.

Diversity of Spatial Analysis Methods in Malaria Modeling

The synthesis results show that there is a diversity of spatial analysis methods used in modeling malaria cases, which can be categorized into four main groups. First, spatial regression methods consisting of Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR) have been proven effective in identifying spatial variations in the relationship between environmental factors and malaria cases, as applied by Hasyim et al. (2018) in South Sumatra, who found that altitude, distance from forests, and rainfall were significantly correlated with malaria cases but with highly

variable spatial relationships across regions. Fahmi et al. (2022) used multivariate logistic regression and zero-inflated Poisson models to analyze risk factors for imported and indigenous malaria in North Sumatra, finding that a 1% increase in relative humidity increased *Plasmodium falciparum* cases by 12.1%, while a 1-meter increase in altitude decreased *Plasmodium vivax* by 0.8%. Second, spatial and spatiotemporal cluster detection techniques using SaTScan and Global Moran's I test are capable of identifying malaria hotspots with a high degree of accuracy, as done by Melchior & Neto (2016) in Acre, Brazil, who detected high-risk clusters in Vale do Juruá, and Gwitira et al. (2020) in Zimbabwe, who found persistent primary clusters in the ti region. Spatial and spatiotemporal cluster detection techniques using SaTScan and Global Moran's I test are capable of identifying malaria hotspots with a high degree of accuracy, as demonstrated by Melchior & Neto (2016) in Acre, Brazil, who detected high-risk clusters in Vale do Juruá, and Gwitira et al. (2020) in Zimbabwe, who found persistent primary clusters in the eastern region during the 6-year study period with temporal patterns reflecting the seasonality of the disease. Third, the Multi-Criteria Decision Analysis (MCDA) approach integrated with GIS through the Analytic Hierarchy Process (AHP) and Weighted Overlay Analysis to produce comprehensive risk maps, as applied by Diriba et al. (2024) in Nekemte, Ethiopia, who classified 37% of the city area (21.4 km²)

as high to very high risk areas, and Zhao et al. (2020) on the Yunnan-Myanmar border, who found that elevation (weight 0.297) and imported cases (weight 0.258) were the strongest predictors of malaria risk with a model that had good predictive capacity based on a high area under the curve. Fourth, descriptive spatial distribution analysis based on GIS was used by three national journals to map malaria case concentrations. Sunarsih et al. (2025) identified that areas with high cases in Muara Enim were generally located near rivers and swamps, which are mosquito habitats. Watmanlusy et al. (2019) found five species of *Anopheles* in West Seram, Maluku, and Hastuty & Setyowati (2021) mapped the distribution of 290 malaria cases in East Sentani District with the highest concentration in RW 3, which is adjacent to forests and wetlands.

Physical Environmental Factors as Key Determinants of Malaria Transmission

An analysis of 10 journals revealed that physical environmental factors play a crucial role in malaria transmission, with altitude/elevation, climate, and proximity to water sources being the most consistent variables with a significant impact. Elevation shows a consistent negative relationship with malaria incidence across various studies, with Hasyim et al. (2018) finding elevation to be a significant predictor in an OLS model in South Sumatra, and Fahmi et al. (2022) quantified that a 1-meter increase in elevation reduced *P. vivax* by 0.8% in North Sumatra, and Zhao et

al. (2020) gave the highest weight (0.297) to elevation in an MCDA model in Yunnan. Climate variables, particularly temperature and humidity, show complex effects on different Plasmodium species, with Fahmi et al. (2022) finding that a 1°C increase in maximum temperature increases *P. falciparum* by 21.0%, but a 1°C increase in minimum temperature actually reduces *P. vivax* by 16.7%, while humidity has a significant effect ($p=0.003$, $PR=3.421$) on malaria incidence, as found by Watmanlusy et al. (2019) in Maluku. Rainfall was also found to be significantly correlated with malaria cases in the global OLS model developed by Hasyim et al. (2018), indicating its role as an important factor in malaria risk modeling. Proximity to water sources emerged as a very strong factor influencing malaria transmission, with Watmanlusy et al. (2019) finding that the distance from mosquito breeding sites was highly significant ($p=0.000$, $RP=10.054$), Sunarsih et al. (2025) identified high case concentrations near rivers and swamps as mosquito habitats in Muara Enim, and Zhao et al. (2020) assigned a weight of 0.175 to water bodies in the MCDA model. Other environmental factors that also have an effect are the distance from forests, which is significant in the OLS model with a weight of 0.041 in the risk model, as well as topography and slope, which affect the variation of *Anopheles* species, as found by Ngadino et al. (2024) in East Java, where *An. sundanicus* is more common in coastal areas, while *An.*

maculatus is more common in valleys and rice fields.

Sociodemographic and Occupational Characteristics as Risk Factors

Findings from various studies indicate that the sociodemographic and occupational characteristics of the population contribute significantly to the risk and spatial distribution of malaria. The productive and adult age groups show varying risk patterns depending on the geographical context, where Fahmi et al. (2022) identified that for imported malaria in North Sumatra, the 19-30 age group had a 3.31 times higher risk, the 31-45 age group had a 5.69 times higher risk, and those over 45 years old have a 5.11 times higher risk compared to the reference group, while Melchior & Neto (2016) found that individuals under 19 years old and women show high incidence in Vale do Juruá, but working-age men are most affected in Vale do Acre, Brazil. In Indonesia, Hastuty & Setyowati (2021) reported that the 15-64 age group accounted for 52.1% of total cases in Jayapura, with a predominance of males (53%), which is consistent with occupational patterns where men are more likely to work in high-risk areas. Occupation emerged as a very strong risk factor, with dramatic findings from Fahmi et al. (2022) that military personnel have a 1,154 times higher risk ($AOR=197.03$) of being infected with imported malaria, while forest and mine workers have a 44 times higher risk ($AOR=44.16$) compared to office workers and traders, indicating that occupations involving

intensive exposure to malaria-endemic environments are a major risk factor. Population mobility has also been shown to be an important determinant in the spatial distribution of malaria, with Zhao et al. (2020) assigning a high weight (0.258) to imported cases in the MCDA risk model at the Yunnan-Myanmar border, and Ngadino et al. (2024) identified that the uneven distribution of imported malaria cases in East Java was caused by the mobility of workers from outside the region, indicating that human movement between endemic and non-endemic areas can maintain transmission even in areas that have achieved elimination. Population density, despite having a relatively lower weight (0.043) in the MCDA model, remains an important social factor in risk mapping as identified by Diriba et al. (2024), indicating that areas with high population density require special attention in the allocation of malaria control resources.

The Role of Access to Health Services and Infrastructure in Malaria Control

Access to health services and public infrastructure has a significant influence on the effectiveness of malaria control and risk distribution, based on a synthesis of the analyzed journals. Distance to health facilities emerged as an important factor in malaria risk modeling, with Zhao et al. (2020) assigning a weight of 0.033 to the variable of distance to health facilities in the MCDA model in Yunnan, while Diriba et al. (2024) included access to health services as one of the main

social factors in risk mapping in Nekemte, Ethiopia, indicating that the affordability of health services affects the ability to detect, diagnose, and treat malaria early, which in turn affects the intensity of transmission in an area. Access to road infrastructure is also considered in risk modeling, albeit with a relatively low weight (0.030) as applied by Zhao et al. (2020), but it remains important because transportation infrastructure affects population mobility, access to health services, and the distribution of malaria control interventions. The level of urbanization, which was given a weight of 0.036 in the MCDA model by Zhao et al. (2020), shows that urban versus rural characteristics affect malaria risk, with rural areas with limited access to health services and infrastructure tending to have higher risks. Ngadino et al. (2024) emphasize the importance of an ecosystem-based approach to malaria control and the need to improve access to health services and community education, recognizing that structural factors such as the availability and affordability of health services not only influence case distribution but also determine the effectiveness of malaria elimination programs. These findings underscore that malaria control interventions cannot focus solely on epidemiological and entomological aspects, but must integrate improvements in access to health services and supporting infrastructure as integral components of a comprehensive and sustainable malaria elimination strategy.

Spatial and Temporal Heterogeneity of Malaria Transmission

One consistent finding across all analyzed journals is the high spatial and temporal heterogeneity in malaria transmission, which has important implications for control program design. Spatial variation in the relationship between environmental factors and malaria cases is clearly demonstrated by Hasyim et al. (2018) through the application of a GWR model in South Sumatra, which revealed that although the variables of altitude, distance from forests, and rainfall were globally significant in the OLS model, the relationship between malaria and these environmental factors varied greatly spatially across regions, indicating that a one-size-fits-all approach would not be effective in malaria control and that strategies must be tailored to the local characteristics of each region. The existence of persistent geographical hotspots over a long period of time was confirmed by Gwitira et al. (2020) in Zimbabwe, where primary malaria clusters were consistently detected in the eastern region during the 6-year study period with significant positive spatial autocorrelation ($p < 0.05$), indicating that malaria transmission tends to be concentrated in specific geographic locations that have conditions conducive to vector breeding and parasite transmission. Fahmi et al. (2022) identified that both indigenous and imported malaria are limited to certain districts and cities in North Sumatra with different hotspots for each type of malaria, where

indigenous hotspots are reported in Tanjung Balai City and Asahan District, while imported hotspots are in Batu Bara, Tebing Tinggi City, Serdang Bedagai, and Simalungun, indicating that the spatial pattern of malaria can vary based on the source of infection.

The temporal dimension of malaria transmission also shows complex and varied patterns between regions, with Gwitira et al. (2020) finding that the temporal pattern of malaria in Zimbabwe reflects the seasonality of the disease, where clusters are detected in certain months of the year, consistent with the vector's life cycle, which is influenced by the rainy and dry seasons. Melchior & Neto (2016) analyzed long-term trends from 1992 to 2014 in Acre, Brazil, finding that malaria mortality rates showed a downward trend across the state, but the case fatality rate increased only in the Rio Branco micro-region, indicating that despite overall improvements, some areas may experience deterioration requiring specific interventions. Variations based on parasite species also show different spatial and temporal patterns, with Fahmi et al. (2022) identifying that *P. falciparum* increases with humidity and maximum temperature, while *P. vivax* decreases with altitude and minimum temperature, indicating that the two species have different ecological niches and require tailored control approaches. Melchior & Neto (2016) also found that malaria case and death patterns varied according to age, sex, and parasite species in different regions of Acre, concluding that malaria is a focal disease with

complex spatial and spatiotemporal patterns influenced by regional characteristics, so disease control strategies must be tailored to these regional characteristics to achieve maximum effectiveness in malaria elimination programs.

Implications of Anopheles Vectors on Spatial Malaria Transmission

The presence and spatial distribution of *Anopheles* vector species appear to be crucial determinants in malaria transmission, with vector species and density variations greatly influenced by local environmental characteristics. Ngadino et al. (2024) identified two main *Anopheles* species in East Java, namely *An. sundaicus* and *An. maculatus*, which have different habitat preferences, with *An. sundaicus* being more common in coastal areas (lagoons), while *An. maculatus* is more commonly found in valleys and rice fields, indicating that regional topography directly influences vector species composition, which in turn affects the intensity and pattern of malaria transmission in various geographical zones. Environmental factors such as regional topography, temperature, humidity, and rainfall have been shown to influence *Anopheles* species variation, with implications that changes in environmental conditions can alter vector composition and distribution, which in turn affects the risk of malaria transmission in a region. Watmanlusy et al. (2019) found five species of *Anopheles* in West Seram District, Maluku, namely *Anopheles vagus*, *Anopheles teselaltus*,

Anopheles koichi, *Anopheles barbirotris*, and *Anopheles farauti*. However, interestingly, based on PCR test results, these species have not been confirmed as malaria vectors in the region despite 41 positive malaria cases, indicating the complexity of identifying competent vectors and the possibility of other unidentified vector species or more complex transmission dynamics involving factors other than vector presence.

Anopheles vector density shows a highly significant influence on malaria incidence, with Watmanlusy et al. (2019) finding that *Anopheles* sp. density had a highly significant effect ($p=0.001$, $PR=2.853$) on malaria incidence in West Seram, indicating that areas with high vector density have a much greater risk of transmission and require intensive vector control interventions. Environmental factors affecting vector density include air temperature ($p=0.022$, $PR=2.082$) and humidity ($p=0.003$, $PR=3.421$), confirming that microclimate conditions are crucial in determining vector populations. The distance from mosquito breeding sites emerged as the strongest factor influencing malaria risk, with a p -value of 0.000 and an RP of 10.054, indicating that proximity to breeding sites such as puddles, swamps, and other bodies of water dramatically increases the risk of mosquito bites and malaria transmission. The findings of Sunarsih et al. (2025) reinforce this by identifying that areas with high concentrations of malaria cases in Muara Enim are generally located near rivers and swamps, which are

ideal habitats for mosquito breeding, and that vegetation in areas such as plantations, rice fields, wetlands, and shrubs can be used by mosquitoes as resting places, creating conditions conducive to the persistence of vector populations. Hastuty & Setyowati (2021) also found that the homes of malaria patients in East Sentani District were located near forests and wetlands where there were puddles and pools of water that could become breeding sites for *Anopheles* sp. larvae, underscoring the importance of environmental management and breeding site elimination as effective vector control strategies in comprehensive malaria elimination programs.

The Contribution of Geospatial Technology in Risk Mapping and Decision Making

This systematic review reveals that geospatial technology, particularly Geographic Information Systems (GIS), has made a substantial contribution to malaria risk mapping and supports evidence-based decision making for control programs. Diriba et al. (2024) demonstrated that malaria risk maps generated through geospatial analysis were able to identify with precision that 18.2% (10.5 km²) of the Nekemte City study area was at very high risk, 18.8% (10.9 km²) at high risk, 30.4% (17.8 km²) at moderate risk, 19.8% (11.5 km²) at low risk, and 12.6% (7.3 km²) at very low risk, with a combined 37% (21.4 km²) of the city classified as high to very high risk areas that are priorities for intervention. This risk map offers a valuable tool for malaria control and elimination efforts in Nekemte

City because by identifying high-risk areas, the map provides actionable insights that can guide local health strategies, optimize the distribution of often limited resources, and improve the efficiency of interventions by focusing efforts on the locations that need them most. Zhao et al. (2020) showed that the integration of spatial MCDA with GIS, which combines multiple environmental factors in disease risk estimation using decision rules derived from existing knowledge or hypothetical understanding of risk factors through various quantitative and qualitative criteria using expert-driven qualitative from experts can produce accurate MCDA risk models and maps, where the developed expert-based models have good predictive capacity with high area under the curve and can help focus elimination efforts on specific locations identified as high risk.

The ability of geospatial technology to perform spatiotemporal analysis provides an important additional dimension in understanding the dynamics of malaria transmission. with Melchior & Neto (2016) using SaTScan to detect spatial and spatiotemporal clusters and visualization with choropleth maps that allow simultaneous identification of temporal and spatial patterns, providing a more comprehensive understanding of how malaria evolves in space and time. Gwitira et al. (2020) demonstrated the use of GIS and spatial scan statistics on passive malaria data from health facilities combined with the Global Moran's I test to test

spatial autocorrelation and retrospective spatial and space-time analysis with a discrete Poisson model for cluster detection, resulting in a deep understanding of the spatial heterogeneity of malaria and the persistence of clusters in certain geographical areas. Ngadino et al. (2024) emphasized that findings from spatial analysis of malaria cases and *Anopheles* species provide important insights for developing more effective and sustainable health policies in efforts to maintain malaria elimination areas in East Java, underscoring that an ecosystem-based approach to malaria control and the need to improve access to health services and community education must be informed by strong spatial evidence. Overall, the 10 journals analyzed show that geospatial technology is not only a technical tool for mapping, but an integral platform for multisectoral data integration, complex risk factor analysis, identification of intervention priorities, program monitoring and evaluation, and communication of results to stakeholders and policymakers, all of which are essential for achieving ambitious malaria elimination targets in diverse geographical and epidemiological contexts.

LIMITATIONS

While this systematic review highlights the utility of GIS in malaria modeling, several limitations must be acknowledged. Regarding the reviewed studies, most rely heavily on passive, secondary surveillance data that may suffer from underreporting, and many exhibit

geographical bias with highly localized study areas that limit the generalizability of their spatial models. Furthermore, entomological components within some studies often lack molecular validation (such as PCR testing) to definitively establish vector competency under local conditions. Regarding the limitations of this systematic review itself, the search was restricted to specific databases (Scopus, PubMed, OpenAlex, and Google Scholar) and strict accreditation criteria (Scopus Q1–Q4 and SINTA 1–2) within a defined timeframe (2016–2025). This may have excluded relevant grey literature, local government reports, or research published in lower-tier local journals, which could otherwise provide valuable micro-level context for malaria elimination planning in high-endemic areas like Sorong City.

CONCLUSION

This systematic literature review successfully synthesized scientific evidence from 10 journals (7 Scopus-indexed and 3 Sinta-indexed) published between 2016–2025, revealing that spatial modeling of malaria using Geographic Information Systems (GIS) is a powerful and essential approach for understanding the complexity of malaria transmission. The analysis identified four main categories of spatial methods: spatial regression (OLS and GWR), cluster detection techniques (SaTScan and Global Moran's I), Multi-Criteria Decision Analysis (MCDA) integrated with GIS, and descriptive spatial

distribution analysis. Key determinants of malaria transmission include physical environmental factors (elevation, temperature, humidity, rainfall, proximity to water sources), sociodemographic characteristics (age, gender, occupation, population mobility), access to health services and infrastructure, and the presence and density of *Anopheles* vector species. The high spatial and temporal heterogeneity of malaria transmission across different regions underscores that one-size-fits-all control strategies are ineffective, and interventions must be tailored to local characteristics, with GIS-based risk maps providing actionable insights for evidence-based decision making in optimizing resource allocation and prioritizing high-risk areas for malaria control and elimination programs.

However, this review has several limitations that should be acknowledged. First, the small number of included studies (n=10) and their geographic concentration in only a few countries (Indonesia, Brazil, Ethiopia, Zimbabwe, and China) limit the generalizability of findings to other malaria-endemic regions, particularly Southwest Papua where local ecological and sociodemographic conditions may differ substantially. Second, the heterogeneity in spatial analysis methods, study designs, and reported outcome measures across the included studies precluded a quantitative meta-analysis, restricting this review to a narrative and descriptive synthesis. Third, most of the reviewed studies relied on secondary data from health facility records,

which may be subject to underreporting or diagnostic inconsistencies, particularly in remote and underserved areas. Several important research gaps remain open for future investigation, including the limited application of advanced spatiotemporal modeling techniques that integrate real-time climate and mobility data, the scarcity of studies examining the interaction between vector behavior and land-use change in eastern Indonesian contexts, and the absence of validated, region-specific GIS-based risk prediction models for Papua and West Papua. Future research should prioritize longitudinal spatial studies incorporating high-resolution environmental and population mobility data specific to Sorong City and similar high-endemic settings in eastern Indonesia to bridge these gaps and strengthen the evidence base for targeted malaria elimination strategies.

SUGGESTION

Based on the results of this systematic literature review, it is recommended that Geographic Information Systems (GIS)-based spatial modeling be integrated into the malaria surveillance system in Sorong City to identify high-risk areas and more precisely target interventions. Local governments and health agencies need to strengthen human resource capacity in spatial analysis and integrate epidemiological, environmental, and climate data into malaria elimination program planning. For future researchers, the development of spatiotemporal models and

more advanced analytical approaches is recommended to produce more accurate risk

maps and support evidence-based policy-making.

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