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SPATIAL ANALYSIS OF MALARIA RISK AND SOCIOECONOMIC DETERMINANTS IN PAPUA PROVINCE, INDONESIA USING A BAYESIAN MODELING APPROACH

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ABSTRAK

Abstract:
Malaria remains a major public health problem in tropical regions, including Indonesia's Papua Province, which bears one of the highest national burdens. This study analyzes the spatial distribution of malaria and identifies key socioeconomic, geographic, and demographic predictors in Papua in 2022 using Bayesian spatial modeling. Secondary data from 28 districts/cities were analyzed with a Bayesian spatial model using the BYM2 formulation and Integrated Nested Laplace Approximation (INLA). Significant spatial disparities were identified, with high-risk clusters in the northeast and central regions. The number of polyclinics showed a significant negative association with malaria incidence, indicating a protective effect. Conversely, regional income and average years of schooling were positively associated with malaria, possibly reflecting increased mobility, detection bias, and development-related ecological change. These findings highlight strong spatial heterogeneity and multifactorial drivers of malaria transmission. Bayesian spatial modeling provides important insights for policy planning and supports the need for geographically targeted, multisectoral interventions, strengthening primary healthcare infrastructure, and context-sensitive development strategies to reduce malaria burden.

***Abstrak*:**
Malaria masih menjadi masalah kesehatan masyarakat utama di wilayah tropis, termasuk Provinsi Papua, yang memiliki salah satu beban malaria tertinggi di Indonesia. Penelitian ini menganalisis distribusi spasial malaria dan mengidentifikasi faktor sosioekonomi, geografis, dan demografis yang berpengaruh di Papua tahun 2022 menggunakan pemodelan spasial Bayesian. Data sekunder dari 28 kabupaten/kota dianalisis dengan model Bayesian menggunakan formulasi BYM2 dan Integrated Nested Laplace Approximation (INLA). Ditemukan ketimpangan spasial yang signifikan, dengan klaster risiko tinggi di wilayah timur laut dan tengah. Jumlah poliklinik berasosiasi negatif secara signifikan dengan kejadian malaria, menunjukkan efek protektif. Sebaliknya, pendapatan wilayah dan rata-rata lama sekolah berhubungan positif dengan malaria, yang kemungkinan terkait dengan mobilitas, bias deteksi, dan perubahan ekologi akibat pembangunan. Temuan ini menegaskan heterogenitas spasial dan faktor multifaktorial penularan malaria serta pentingnya intervensi multisektoral yang terarah secara geografis, penguatan layanan kesehatan primer, dan perencanaan pembangunan yang sensitif konteks.

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INTRODUCTION

Malaria remains one of the major infectious diseases in tropical regions, with significant global health implications. According to the WHO report, approximately 241 million malaria cases were recorded worldwide in 2020, resulting in around 627,000 deaths [1] As transmission intensity decreases, the distribution of malaria risk has become increasingly localized and fragmented, often concentrated in specific regions or population groups [1] In other words, malaria transmission is becoming more heterogeneous, frequently forming "hot-spots" in particular areas.

Various socioeconomic and demographic factors play a role in shaping the pattern of malaria distribution. Emphasize that "Malaria is still an important parasitic infectious disease that affects poor and vulnerable communities in many developing countries, including Indonesia," indicating that the disease tends to affect impoverished and vulnerable populations [2]. In Papua, found that rural populations and those living in poor, densely forested, and lowland districts are at higher risk of infection than other groups. They also noted that "malaria is geography-dependent in Indonesian Papua; it is also a disease of poverty." This suggests that geographic location (such as limited access and environmental characteristics) and poverty are critical determinants of malaria transmission in the region [3]. Also emphasized the variation in local determinants across provinces, highlighting the need for locally tailored interventions [2].

In the context of malaria epidemiology, spatial analysis and Bayesian approaches have become increasingly essential. Numerous studies have shown that malaria transmission tends to form clear spatial clusters. For example, through geographically weighted regression, identified malaria hot-spots around Lake Victoria and the eastern coast of Kenya, while areas like Nairobi were identified as cold-spots with low case numbers. In Papua, surveillance-based studies also show highly unequal malaria distribution [1] therefore, advanced analytical methods such as the Bayesian spatio-temporal model are highly relevant for mapping the complex patterns of malaria transmission. "Bayesian spatio-temporal analysis is an advanced and comprehensive methodological approach for modelling complex disease patterns, such as those observed in malaria transmission." [4]. This approach enables researchers to simultaneously analyze spatial and temporal components, along with environmental, climatic, and socioeconomic factors, within a single modeling framework. Consequently, Bayesian spatio-temporal methods provide deeper insights into the dynamics and determinants of malaria transmission—critical information for designing more effective interventions and control strategies, particularly in endemic areas like Papua.

This article aims to investigate the influence of geological, social, and demographic factors on the increasing number of malaria cases in Indonesia, with a particular focus on Papua, which according to the 2022 BPS data, represents the largest malaria-endemic region in the country. In this study, statistical analysis is conducted using the Bayesian spatial modeling approach.

The use of the Bayesian spatial modeling approach in this study is justified by the geographically dependent nature of malaria transmission in Papua. Malaria cases are not distributed evenly but tend to form clusters or "hot-spots" in certain ecological and social settings, which cannot be adequately captured by standard regression models that assume independence between observations. The Bayesian framework, particularly the Besag–York–Mollié 2 (BYM2) model, allows researchers to incorporate both structured spatial effects accounting for similarities among neighboring districts and unstructured random effects to capture local heterogeneity. This is especially important in Papua, where ecological conditions such as wetlands, forests, and coastal lowlands interact with socioeconomic disparities to produce uneven transmission risks. Moreover, the Bayesian approach offers the advantage of smoothing risk estimates in areas with sparse data by "borrowing strength" from neighboring regions, thereby reducing random noise while preserving true patterns of malaria risk. The Integrated Nested Laplace Approximation (INLA) further enables efficient computation, making it feasible to generate reliable risk maps and credible intervals for each district. These outputs provide not only point estimates but also measures of uncertainty, such as exceedance probabilities, which are critical for guiding health policy and prioritizing interventions. In this way, Bayesian spatial modeling provides a robust and practical analytical framework for understanding malaria epidemiology in Papua and for informing resource allocation in malaria control programs.

RESEARCH METHOD

1. Study Area and Data

The study area in this research is Papua Province, which covers an area of 82,681 km². The research focuses on one municipality and 27 regencies within Papua Province. The variables used in this study consist of independent and dependent variables. Data for both types of variables were obtained from the Central Bureau of Statistics, specifically from the Papua in Figures 2023 report. The dependent variable in this study is the number of malaria cases in Papua in 2022. Meanwhile, the independent variables include elevation, distance to the provincial capital, regional income, labor force population, number of hospitals, number of polyclinics, number of community health centers (puskesmas), number of auxiliary community health centers (puskesmas pembantu), average years of schooling, school participation rate, number of coastal villages, number of valleys, number of slopes, and number of lowland villages.

Bayesian Spasial Modeling with INLA. In this study, a spatial regression model was employed to examine the potential linear relationship between the response variable and explanatory covariates. Let $Y_i$represent the observed count (assumed to follow an independent Poisson distribution), E_i is the expected count, and θ_i is the relative risk for *i* area:
$Y_i \sim Poisson(E_i\theta_i), i = 1, \ldots, n.$

Where:
$$\log(\theta_i) = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + u_i + v_i,$$

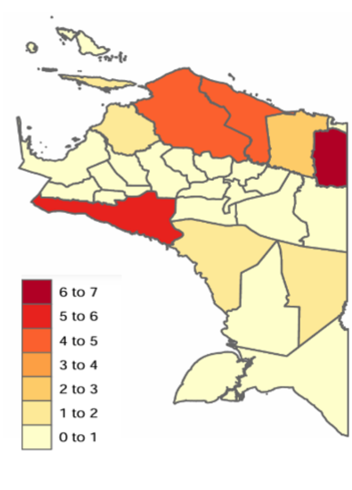
Here, β_0 is the intercept representing the overall risk, β_n is the coefficient for the *n*-th covariate,u_i is the structured spatial component modeled using a Conditional Autoregressive (CAR) distribution, $u_i|u_{-i} \sim N\left(\bar{u}_{\delta}, \frac{\sigma_u^2}{n_{\delta_i}}\right)$ and v_i is the unstructured spatial effect defined as $v_i \sim N(0, \sigma_v^2)$. The relative risk $(\theta_i > 1)$ indicates whether *i-th* area has a higher $(\theta_i > 1)$ or lower $(\theta_i < 1)$ risk than the standard population average [5]. For the values included in the Bayesian model, the researcher used INLA as the inference method.

2. INLA

Integrated Nested Laplace Approximation (INLA) is a numerical method used for performing Bayesian inference in complex hierarchical models, particularly latent Gaussian models [6], [7], [8], [9] [30]. INLA allows for more flexible and computationally efficient modeling than traditional Bayesian inference techniques, offering faster computation times and more accurate results [10]. It is widely applied across disciplines such as epidemiology, ecology, and social sciences for analyzing complex data and estimating parameters in hierarchical models [11].

RESULT AND ANALYSIS

1. Result



Kota/Kab	RR
Keerom	6,485735447
Mimika	5,694673592
Mamberamo Raya	4,828418575
Sarmi	4,307621075
Jayapura	2,728980471
Kepulauan Yapen	1,670098279
Waropen	1,615504396
Boven Digoel	1,488714352
Asmat	1,382831475
Kota Jayapura	0,997847887
Yahukimo	0,655171376
Mappi	0,549200559
Pegunungan Bintang	0,283967038
Nabire	0,245909697
Biak Numfor	0,177771891
Puncak	0,141195429
Merauke	0,073767838
Supiori	0,034017932
Jayawijaya	0,028090857
Yalimo	0,01664646
Intan Jaya	0,010981222
Paniai	0,010393286
Lanny Jaya	0,008217157
Puncak Jaya	0,005924526
Mamberamo Tengah	0,004071958
Deiyai	0,00406648
Dogiyai	0,000186822
Nduga	0,000136273
Tolikara	9,27635E-05

Figure 1. Statistical Mapping of Malaria Relative Risk (RR) in Papua Province, 2022

Table 1.
Results of Bayesian Regression Parameter Estimates

Variable	Mean	SD	2.5% Quantile	50% Quantile	97.5% Quantile
Intercept	-10.1181	3.48158	-17.34294	-10.0016	-3.56125
Elevation	-0.00166	0.00112	-0.003901	-0.00166	0.0005429
Distance to the Provincial Capital	-0.00517	0.00396	-0.0133451	-0.00509	0.002515
Regional Income	7.24E-09	2.20E-09	2.985E-09	7.18E-09	1.18E-08
Labor Force Population	1.61E-05	1.70E-05	-1.612E-05	1.58E-05	4.97E-05
Hospitals	-0.63584	0.44233	-1.528038	-0.63017	0.2242937
Polyclinics	-0.76848	0.35576	-1.50092	-0.75865	-0.0921282
Community Health Centers (Puskesmas)	-0.08457	0.14062	-0.3676139	-0.08303	0.189558
Auxiliary Community Health Centers (Puskesmas Pembantu)	-0.03866	0.02246	-0.0844934	-0.03818	0.0045133
Average Years of Schooling	1.072322	0.36952	0.3692763	1.06239	1.832333

The statistical mapping of the relative risk (RR) of malaria across Papua Province in 2022 revealed significant geographic disparities in infection risk. The districts of Keerom and Puncak Jaya exhibited the highest risk levels. Keerom recorded an RR of 6.4857, visually represented in dark red on the map, indicating a risk category between 6 and 7. Similarly, Mimika had an RR of 5.6946, represented in red, corresponding to a 5–6 risk category.

Other districts with high RR values included Mamberamo Raya (4.8284), Sarmi (4.3076), and Jayapura (2.7289), which fell into moderate-to-high risk categories. Spatially, these high-risk zones were concentrated in the northeast, central-north, and parts of the southern region of the province, represented by a gradient from orange to deep red on the map.

Bayesian spatial model analysis from Table 1 revealed that among all tested predictor variables, only regional income, number of polyclinics, and average years of schooling demonstrated a statistically significant influence on malaria case counts. This conclusion was based on the 95% credible interval (ranging from the 0.025 to 0.975 quantiles), which did not include zero for these variables. Specifically, regional income per district (interval: 2.98×10^{-9} to 1.18×10^{-8}) and average years of schooling (interval: 0.369 to 1.83) were positively correlated with malaria incidence. Conversely, the number of polyclinics (interval: –1.5 to –0.0921) exhibited a significant negative effect, indicating a reduction in malaria cases with increased polyclinic availability.

Other variables such as elevation, distance to the provincial capital, size of the working-age population, number of hospitals, number of public health centers (puskesmas), and number of auxiliary health centers did not show statistically significant effects, as their 95% credible intervals included zero.

2. Analysis

The concentration of high RR in northern Papua is likely influenced by a combination of geographical, environmental, climatic, socioeconomic, and demographic factors. Geographically, northern Papua is characterized by lowlands, coastal regions, and wetland ecosystems, which are ideal breeding grounds for *Anopheles* mosquitoes, the primary vectors of malaria. In contrast, the central and southern areas are mountainous with lower temperatures that inhibit the life cycle of *Plasmodium* parasites.

The region's wet tropical climate, with consistently high rainfall and humidity, supports mosquito survival and parasite development. Additionally, dense tropical forests in northern Papua serve as shelters for mosquitoes, facilitating vector proliferation.

Demographically, high population mobility particularly in urban hubs such as Jayapura can increase malaria transmission from endemic to susceptible populations [13]. Mimika, with the second-highest RR, is a major mining center (PT. Freeport), attracting large-scale migration and increasing the risk of imported infections. Mining activities also contribute to environmental changes such as deforestation and open-pit mining, which expand mosquito habitats [14], [15].

In remote districts such as Keerom and Mamberamo Raya, scattered settlements and limited access to healthcare services result in delayed diagnosis and treatment, increasing the likelihood of secondary transmission. The dominance of *Plasmodium falciparum* and *P. vivax* in these areas further exacerbates the malaria burden [13], [15].

Socioeconomic disparities also contribute to elevated RR values. Districts such as Sarmi and Keerom have moderate Human Development Index (HDI) scores of 67.00 and 69.25, respectively, while Mamberamo Raya has a low HDI of 58.49 [16]. Poverty rates exceeding 30% limit access to preventive tools such as insecticide-treated nets, medications, and adequate housing [17]. Mimika, despite having a high HDI (76.85), also reports high RR, likely due to moderate social inequality reflected by its Gini ratio of 0.344 (BPS-Statistics Indonesia Papua Province, 2024).

Education levels also influence malaria risk. High-RR districts such as Keerom, Mimika, Mamberamo Raya, and Sarmi have relatively low average years of schooling 8.00, 9.91, 5.65, and 8.53 years, respectively [19] which may affect health literacy and preventive behaviors.

3. Practical Implications

The findings of this study provide important practical implications for health workers and policymakers in Papua. The analysis revealed that the number of polyclinics has a significant negative association with malaria incidence, reinforcing the evidence that expanding primary healthcare facilities is highly effective in reducing disease burden. Therefore, resource allocation should prioritize increasing the number of polyclinics, expanding the reach of mobile health services, and strengthening the role of community health workers in high-risk districts such as Keerom, Mimika, Mamberamo Raya, and Sarmi. These interventions should be accompanied by improved logistical access, including the distribution of insecticide-treated nets, rapid diagnostic tests (RDTs), and artemisinin-based combination therapy (ACT) to remote areas. Furthermore, enhancing the capacity of healthcare workers through training in early diagnosis and prompt treatment is essential for interrupting transmission chains.

The study also identified a positive relationship between regional income and average years of schooling with malaria incidence. A practical interpretation of this finding highlights the need for integrated strategies that take into account population mobility driven by economic development and mining activities, as well as the detection bias present in areas with higher education levels. Consequently, health workers must collaborate across sectors, including with mining companies and local stakeholders, to ensure that malaria prevention interventions such as environmental management, housing improvement, and community-based health services are implemented in a sustainable manner.

4. Limitations

This study has several limitations that must be acknowledged. The data are aggregated at the district level, making the results susceptible to ecological fallacy and preventing direct generalization to the individual level. The study covers only one year of observation (2022), which limits its ability to capture seasonal variations or long-term trends in malaria transmission. The quality of case data is likely influenced by under-reporting in remote areas with limited access to health facilities and by detection bias in districts with better healthcare services and higher education levels, which may explain the positive correlation between years of schooling and malaria incidence.

The variables included in the model are limited to socioeconomic and infrastructure indicators, without incorporating important environmental and entomological factors such as rainfall, temperature, humidity, and vector species distribution. In addition, the measure of healthcare infrastructure is based only on the physical number of facilities, without considering their capacity, quality of services, or distribution of medical personnel. Although the BYM2 model captures spatial correlation, the results remain sensitive to the choice of priors, the presence of outliers such as Keerom and Mimika, and potential multicollinearity among predictor variables.

The findings of this study should be interpreted as associative rather than causal. Future research should include longitudinal designs to capture temporal dynamics, more granular analyses at the village level to reduce ecological bias, and the integration of environmental and mobility variables to provide more precise recommendations for malaria control policies in Papua.

DISCUSSION

The positive correlation between regional income and malaria cases in Papua requires interpretation through a complex causal framework. As observed by [20], increased regional income may drive greater population mobility into high-risk areas and expand economic activities into malaria-endemic environments, thereby increasing exposure. Unplanned urban growth and land-use changes associated with economic development can also create additional mosquito breeding habitats [21]. Moreover, rising income does not necessarily guarantee equitable or effective implementation of malaria control programs [22]. These findings indicate that economic development in endemic regions such as Papua must be accompanied by integrated, health-sensitive planning strategies.

Similarly, the positive and significant association between average years of schooling and malaria incidence (95% credible interval: 0.369–1.83) warrants context-sensitive interpretation. One explanation is detection bias, whereby higher education levels lead to increased awareness and utilization of diagnostic services, resulting in more cases being detected and reported [23]. Additionally, higher education is often associated with increased social mobility and migration, potentially exposing individuals to endemic areas or facilitating the importation of malaria cases [24]. Environmental changes linked to development and urbanization may further foster mosquito breeding sites [26];[4].

In contrast, the number of polyclinics demonstrated a significant negative association with malaria incidence (95% credible interval: –1.5 to –0.0921), underscoring the protective role of accessible primary healthcare. Improved proximity to polyclinics facilitates early diagnosis and timely treatment, interrupting transmission chains [27]. Evidence from Kilifi, Kenya, shows that severe malaria incidence more than doubled when travel time to primary care increased from 10 minutes to two hours, while accessible primary healthcare reduced disease burden by up to 66% [28].

Furthermore, integrated malaria services such as insecticide-treated net distribution, community education, and rapid diagnostic testing have demonstrated strong effectiveness. In Myanmar, such interventions reduced *Plasmodium falciparum* cases by 70% and *P. vivax* cases by 64% within one year [29]. These findings emphasize that expanding polyclinic services strengthens not only treatment capacity but also surveillance and community-level prevention, making it a critical strategy for malaria control in Papua Province.

CONCLUSION

This study demonstrates that malaria transmission in Papua Province is spatially heterogeneous and influenced by a complex interplay of geographic, socioeconomic, and demographic factors. The application of Bayesian spatial modeling using the BYM2 approach revealed that among all tested predictors, regional income and average years of schooling were significantly and positively associated with malaria incidence likely due to factors such as increased mobility, urban expansion, and detection bias. In contrast, the number of polyclinics showed a significant negative association, indicating the critical role of accessible primary healthcare services in reducing disease burden.

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