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Spatial analysis-based risk identification for malaria elimination efforts in Papua

Muhammad Iqbal Maulana*
Urban and Regional Planning
Diponegoro University,
Indonesia

Ida Fransiska Pandiangan
Community Nutrition
IPB University,
Indonesia

Ridho Saputra
Social Antropology
University of Indonesia,
Indonesia

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Abstract

Papua is a region grappling with various health issues, particularly malaria. A study revealed that a staggering 92% of national malaria cases are concentrated in Papua. This poses a significant challenge given the Sustainable Development Goals (SDGs) target of malaria elimination by 2030. A risk analysis was conducted to spatially identify the distribution of malaria. This approach employed Geographic Information Systems (GIS) and Remote Sensing, utilizing the Model Builder and weighted overlay methods. The analysis indicated that 91.77% of the region is at a moderate risk, while 0.33% is at a high risk. Targeted interventions are imperative for areas classified as moderate to high risk. Comprehensive prevention strategies must address core challenges such as early detection, case management, treatment, and improved access to healthcare facilities.

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INTRODUCTION

Papua has an area of 418,700 km², an annual precipitation of 2,126.37 mm, an average elevation of 227 meters above sea level, and a population of 5,669,857. Papua, an eastern Indonesian island, faces numerous health challenges. These issues generally stem from individual diseases and suboptimal healthcare facilities. Rencana Induk Percepatan Pembangunan Papua (RIPPP) for 2022-2041 identifies three key health indicators: life expectancy, stunting prevalence, and malaria cases. Malaria, a parasitic disease caused by Plasmodium protozoa and transmitted through the bite of Anopheles mosquitoes (Centers for Disease Control and Prevention, 2017), is a significant concern. A staggering 92% of national malaria cases are concentrated in Papua (Kemenkes RI, 2023). The 2023 Indonesian Health Survey revealed the

***Corresponding Author:**
Muhammad Iqbal Maulana. Urban and Regional Planning/Diponegoro University, INDONESIA,
Email: iqbal.maulana6747@gmail.com

highest malaria prevalence in Papua Province (21.4%) and Central Papua Province (19.3%). Malaria elimination is a national development mandate, aligned with the Sustainable Development Goals target of eliminating malaria by 2030. However, as of 2024, malaria has only been eliminated in Arfak Mountains and South Sorong Districts, according to the Ministry of Health data.

Malaria in Papua has become a significant national concern, necessitating effective interventions for its elimination. Malaria cases can be attributed to four primary factors: mosquito bite transmission, poor quality and access to sanitation, potential transmission through blood transfusions and contaminated needles, and the risk of congenital malaria from pregnant women to their fetuses. A spatial analysis approach was employed, leveraging the power of Geographic Information Systems (GIS) and Remote Sensing (RS). Geospatial technologies have become increasingly prevalent and sophisticated, supporting a wide range of human activities. The benefits of geospatial analysis are widely optimized to support planning, such as network and accessibility analysis, buffer and proximity analysis (Trindade et al., 2023), suitability and land use analysis (Wani et al., 2022), environmental risk and disaster hazard mapping, urban heat island and climate impact analysis (Swayam Vid & Shanti Kumari, 2022), multi-criteria decision analysis (Maantay et al., 2022; Sejati et al., 2023), 3D urban modeling and visualization (Mitchell, 2019), land use change analysis and forecasting (Dewa et al., 2022; Faria de Deus et al., 2021), utility and infrastructure mapping (Marsh et al., 2024), socio-economic mapping (Chauhan & Ghimire, 2023), geospatial data visualization and presentation (Samsonov, 2023), among others.

Chauhan & Ghimire (2023) used a comprehensive geospatial analysis to avoid environmental, and economic losses in urban development plans through solid waste management. This is implemented by determining the optimal location of solid waste development by integrating environmental, social, and economic factors. In the same way, Maji & Sarkar (2019) also used a geospatial approach to understand the development of socio-economic development in Bankura District, West Bengal. This was implemented by assessing the thematic layers for each indicator by weighing the final z-score. Through this analysis of the socio-economic sectors, it was found that the spatial pattern of development in Bankura District is not uniform and shows contrasting differences. Based on geospatial analysis, Maji and Sarkar (2019) divided the level of integrated socio-economic development in West Bengal into four categories, viz: (I) areas that have good conditions (5.6 to 11.5); (II) developing areas with moderate values (0 to 5.6); (III) areas with low values (-5.6 to 0); and (IV) areas with very low values (-8.5 to -5.6). Areas with low to very low scores are caused by poor accessibility and physiographic barriers that slow down development. Meanwhile, areas with good socio-economic conditions have good accessibility and agricultural prospects. In this case, it can be said that spatial databases are an effective approach in development planning because they can present complex data in each region

In the healthcare domain, geospatial technologies have been extensively developed for prevention, monitoring, and evaluation purposes. One of the geospatial analyses in the health sector that has been carried out is the analysis of the local burden of malaria in Kagera region which was carried out through retrospectively data from health facilities and community surveys from 2015-2023 to identify malaria hot spots (Petro et al, 2024). The benefits of geospatial analysis can be optimized to understand disease patterns and influencing factors, prevent diseases by identifying at-risk groups and designing targeted interventions, control diseases by mitigating their impact and preventing outbreaks, and evaluate the effectiveness of programs and make improvements. Prevention efforts can be enhanced through the creation of malaria risk maps, which are expected to provide effective solutions for preventing the spread of malaria. This is particularly relevant considering that malaria can spread when infected individuals move to new locations and act as carriers for others. Malaria risk analysis has taken into account climatic, socio demographic, and clinical factors. The high incidence of malaria in Papua can be measured using various variables such as annual average temperature, annual average rainfall, slope, elevation, Normalized Difference Vegetation Index (NDVI), distance to water bodies, distance to roads, land use and land cover, population density, and malaria prevalence (Ferrao et al., 2018). This research aims to identify the main factors of malaria and analyze malaria risk through spatial analysis. The results of malaria risk analysis are categorized into three classes: low, moderate, and high. Areas classified as moderate to high risk require targeted interventions for malaria prevention. Therefore, malaria risk maps can serve as a valuable planning tool to support malaria elimination efforts in Papua. The refinement of the analysis of each indicator is explained in the method section and the research results are identified based on regional characteristics and human behavior which are explained in the results and discussion section.

METHOD

Modeling using a GIS and Remote Sensing-based spatial analysis approach was employed to map malaria risk areas. This study utilized ten variables to determine malaria risk. The selected variables considered climatic, socio-demographic, and clinical aspects. The study used Model Builder as the analytical framework and weighted overlay as the analysis process, assigning weights to the most influential factors contributing to malaria transmission (Figure 1).

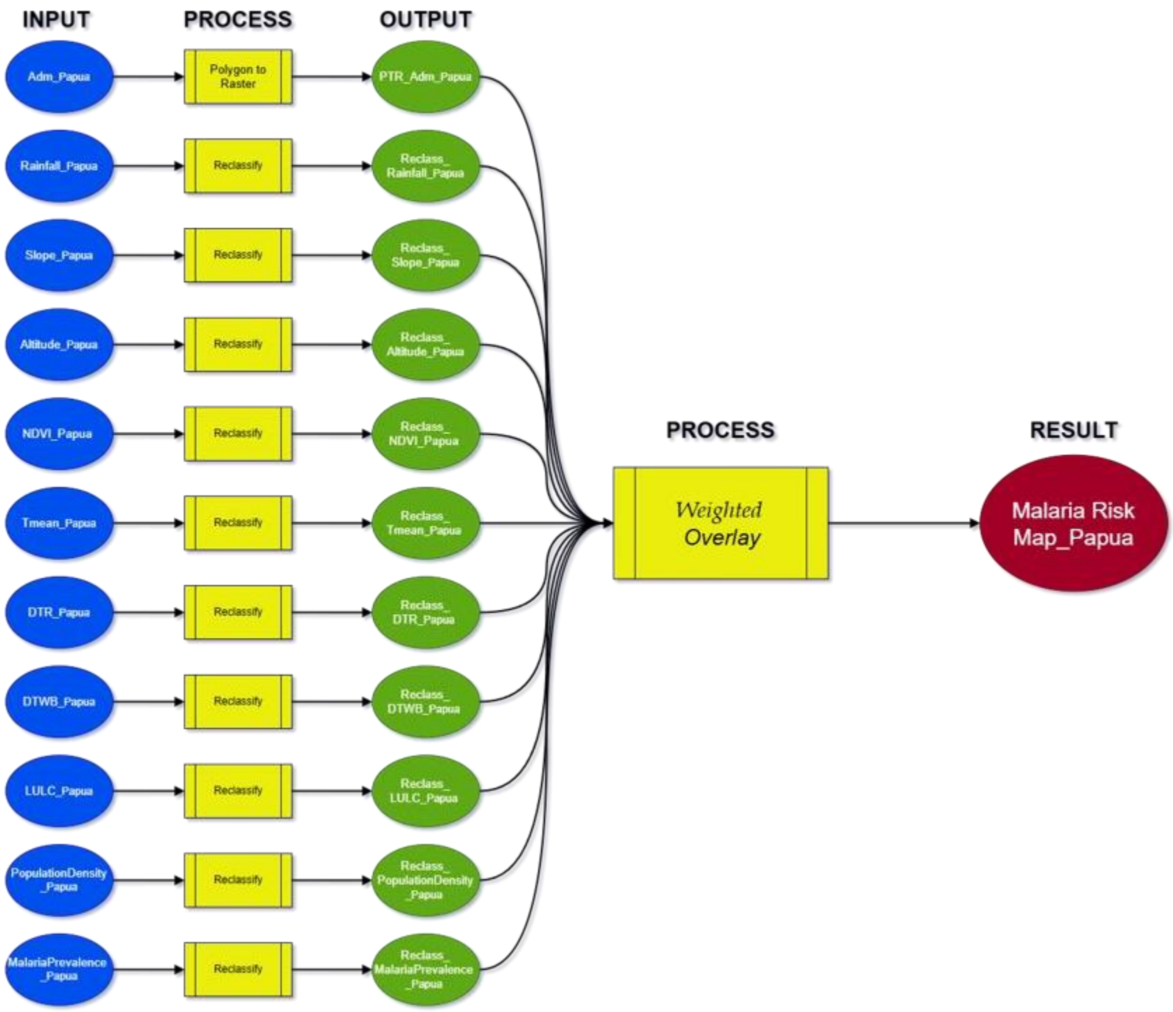


Figure 1. Model builder for malaria risk mapping

The first variable was annual rainfall, calculated as the average annual rainfall from 2018 to January 2024. The highest average annual rainfall in Papua was 6,410.27 mm, while the lowest was 903.32 mm. Areas in Papua with high rainfall include Kaimana Regency (6,410.27 mm), Mimika Regency (5,589.73 mm), Teluk Wondama Regency (5,117.68 mm), Asmat Regency (5.030.64 mm), and Maybrat Regency (4,709.14 mm). Rainfall significantly influences the breeding of malaria-carrying mosquitoes. Rainfall less than 450 mm creates dry conditions unfavorable for mosquito survival, while levels exceeding 1,000 mm are also unsuitable for mosquito breeding. The predominant mosquito species in Papua, An. farauti, is an anthropophilic species with a long lifespan. Therefore, rainfall between 250-700 mm is considered optimal for mosquito survival and breeding (Ferrao et al., 2018). However, this study attempted to reclassify the regions contextually, considering the area's extent and the use of annual data, using the natural breaks method (Figure 2).

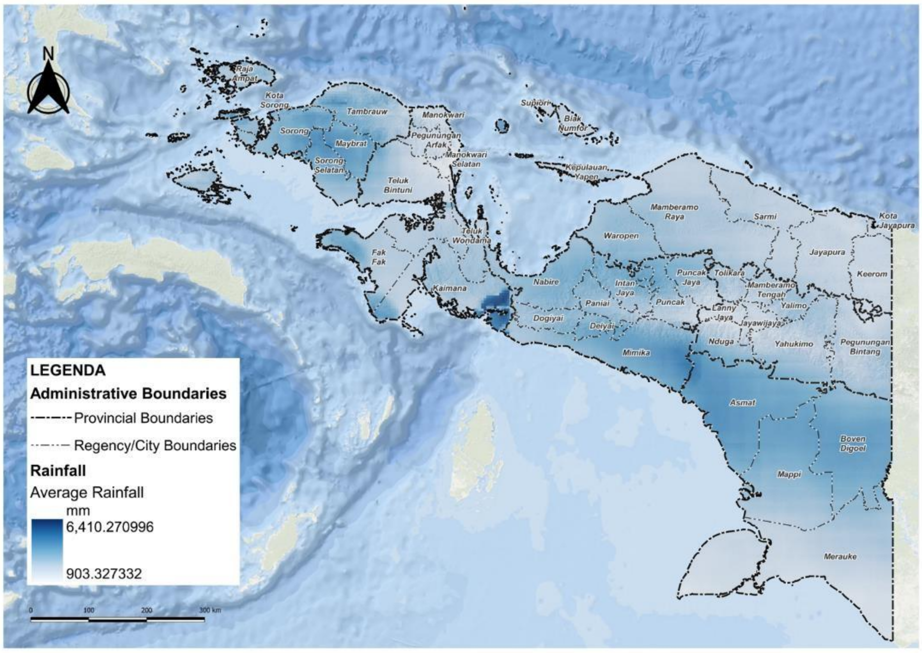


Figure 2. Annual average rainfall map

The second variable was slope. The assumption was that flatter areas are more prone to water accumulation and the formation of stagnant water after rainfall, thus facilitating mosquito breeding (Ferrao et al., 2018). Malaria risk was assessed based on the following slope classifications: 0-5% (high risk), 5-15% (moderate risk), and >15% (low risk). Most of the flat areas in Papua are located in South Papua Province, Papua Province, parts of West Papua Province, and Southwest Papua Province. Consequently, areas at high risk of malaria include Merauke Regency, Mappi Regency, Boven Digoel Regency, Asmat Regency, Mimika Regency, Fakfak Regency, Teluk Bintuni Regency, South Sorong Regency, Mamberamo Raya Regency, and Waropen Regency (Figure 3).

The third variable was elevation. It was assumed that areas below 200 meters (lowland) were classified as the highest risk for malaria, areas between 201-500 meters (highland) were classified as moderate risk, and areas above 500 meters (high hills/mountains) were classified as low risk for malaria exposure. Elevation influences the distribution and spread of malaria as it affects regional temperatures. For every 200-meter increase in elevation, the temperature decreases by 1°C, making highlands cooler than lowlands. However, at certain elevations, malaria transmission does not occur due to extreme temperatures that disrupt the mosquito life cycle (Ferrao et al., 2018). Most of Papua is below 500 meters in elevation, except for Tambrauw Regency, Arfak Mountains Regency, Dogiyai Regency, Paniai Regency, Deiyai Regency, Puncak Regency, Puncak Jaya Regency, Tolikara Regency, Lanny Jaya Regency, Nduga Regency, Jayawijaya Regency, Yalimo Regency, Yahukimo Regency, and Bintang Mountains Regency (Figure 4).

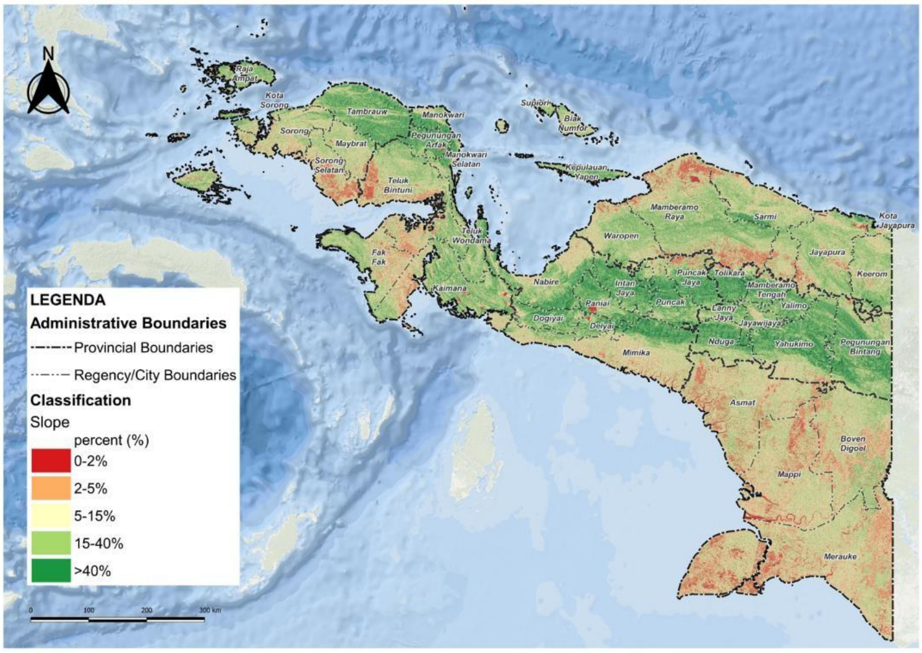


Figure 3. Slope map

The fourth variable was the Normalized Difference Vegetation Index (NDVI), which ranges from -1 to 1, with values closer to 1 indicating higher vegetation density. NDVI analysis was conducted using remote sensing techniques with the aid of Google Earth Engine (GEE). Sentinel-2 data, known for its high-resolution imagery, was employed for this analysis, making it suitable for land monitoring, emergency management, and security applications. The NDVI index measures vegetation health based on the reflectance of light at specific wavelengths (SentiWiki, 2024). NDVI influences mosquito breeding as higher vegetation density facilitates photosynthesis, thereby promoting malaria transmission (Ferrao et al., 2018) (Figure 5).

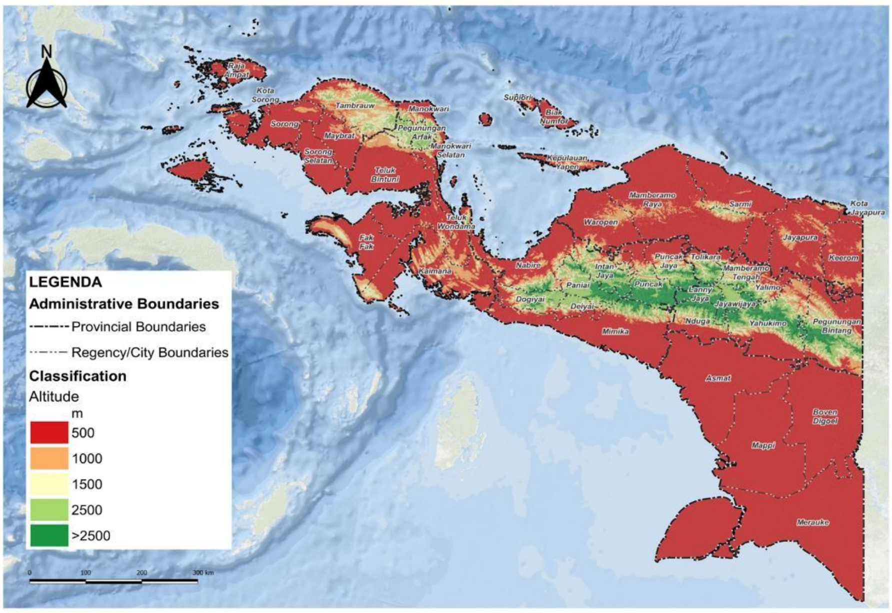


Figure 4. Altitude map

The fifth variable was the mean land surface temperature (LST), calculated using LST data from 2014 to March 2024. LST is a crucial variable in the Earth's climate system as it reflects processes such as energy and water exchange between the land surface and atmosphere, and influences plant growth rates and timing (Esa, 2024). The Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature/Emissivity Daily (MOD11A1) Version 6.1 data with a spatial resolution of 1 km was used for this analysis (Wan, 2024). Temperature is a primary factor in malaria development, as the parasite cannot develop below 18°C or above 40°C. Mosquitoes can survive during the incubation period at temperatures between 28°C and 32°C (Ferrao et al., 2018). However, for this study, to accommodate regional context, area extent, and the use of annual data, a reclassification was performed using the natural breaks method (Figure 6).

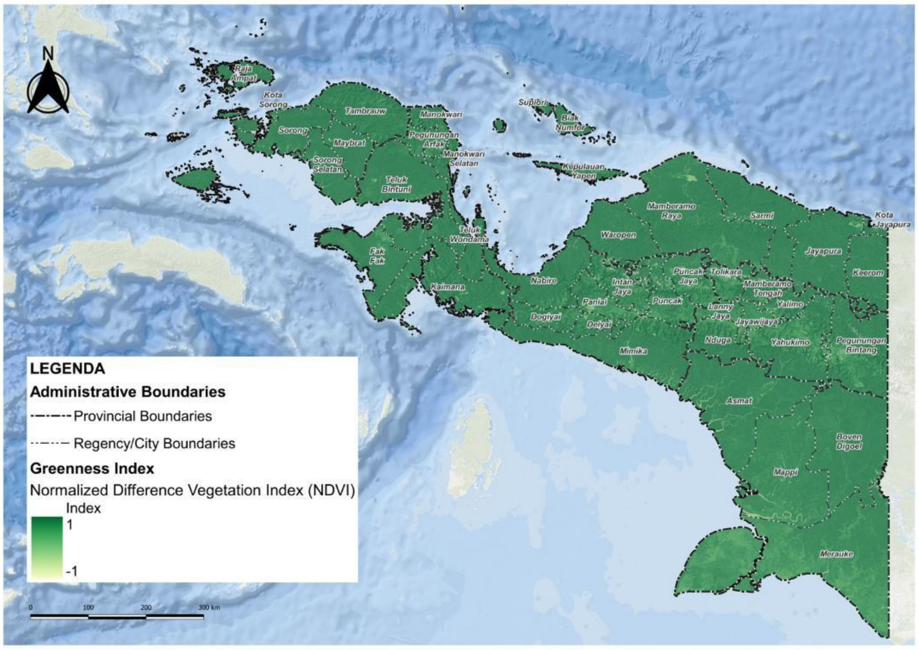


Figure 6. NDVI map

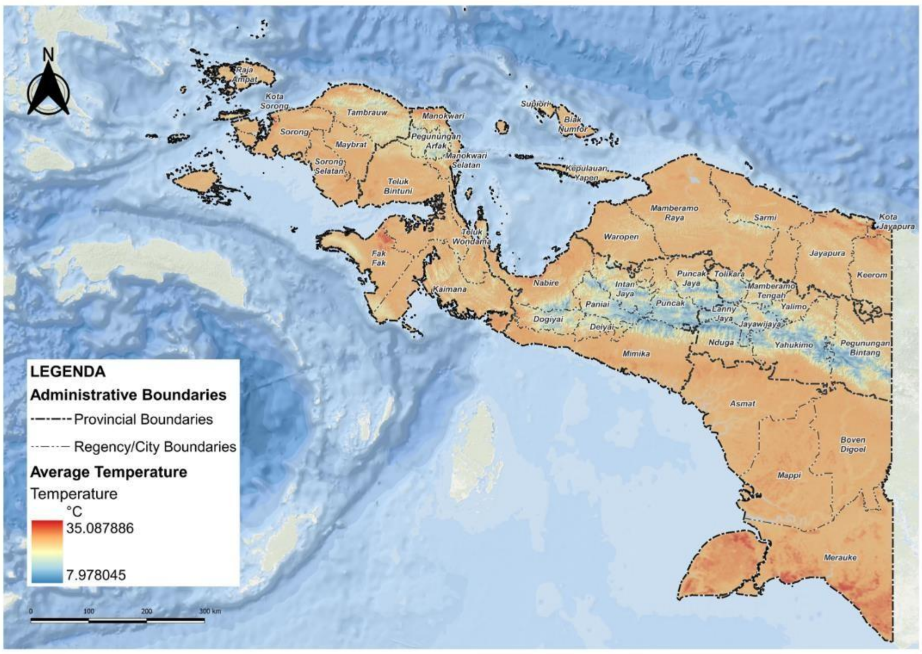


Figure 5. Annual average temperature map

The sixth variable was road network accessibility. The assumption was that closer proximity to roads would improve the effectiveness of malaria intervention efforts. Distance to roads significantly influences the evacuation process of malaria patients to the nearest health facilities. Risk levels were assessed as follows: less than 2.5 km (easily accessible by foot), 2.5-5 km (accessible by bicycle), and greater than 5 km (difficult to access and intervene). A study in Zambia showed that every 500-meter increase in distance from a road was associated with a 5% increase in the risk of malaria (Ferrao et al., 2018) (Figure 7).

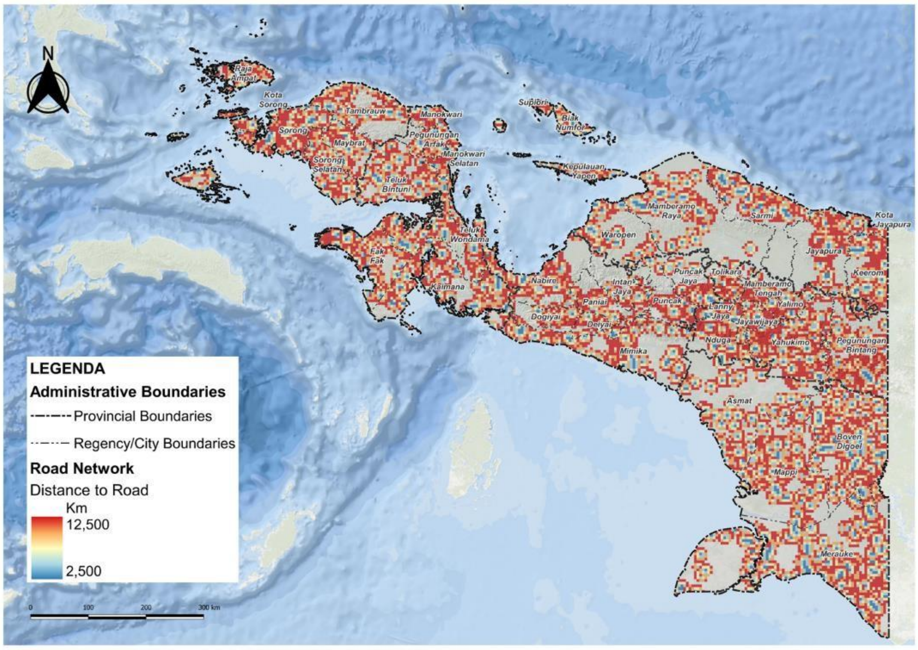


Figure 7. Road network accessibility map

The seventh variable was proximity to water bodies, a primary factor along with temperature, as it plays a crucial role in the breeding of malaria-carrying mosquitoes. Water bodies are a direct indicator of malaria risk. A study in China showed that populations living within 60 meters of a water body had a higher risk of malaria infection. The proximity to water bodies was classified as follows: less than 500 meters (high risk) as the flight range of mosquitoes is 1500 meters, 500-1500 meters (moderate risk) as it is still within the flight range of mosquitoes, and greater than 1500 meters (low risk) as it is beyond the flight range of mosquitoes (Ferrao et al., 2018) (Figure 8).

The eighth variable was Land Use Land Cover (LULC) using data in 2020. Areas with high vegetation, grasslands, and water bodies were considered high-risk for malaria. Shrublands and areas with abundant vegetation were classified as moderate-risk, while forests, bare land, and urban areas were categorized as low-risk. This assessment was based on a study in Kenya that demonstrated a link between land cover types and the presence of Anopheles larvae. Overall, a higher proportion of positive Anopheles habitats were found in grasslands, agricultural land, and wetlands (Ferrao et al., 2018). Most of Papua is still dominated by forests, except for some districts in the Highland and Southern Papua provinces, which are dominated by shrubs, vegetation, and water bodies (Figure 9).

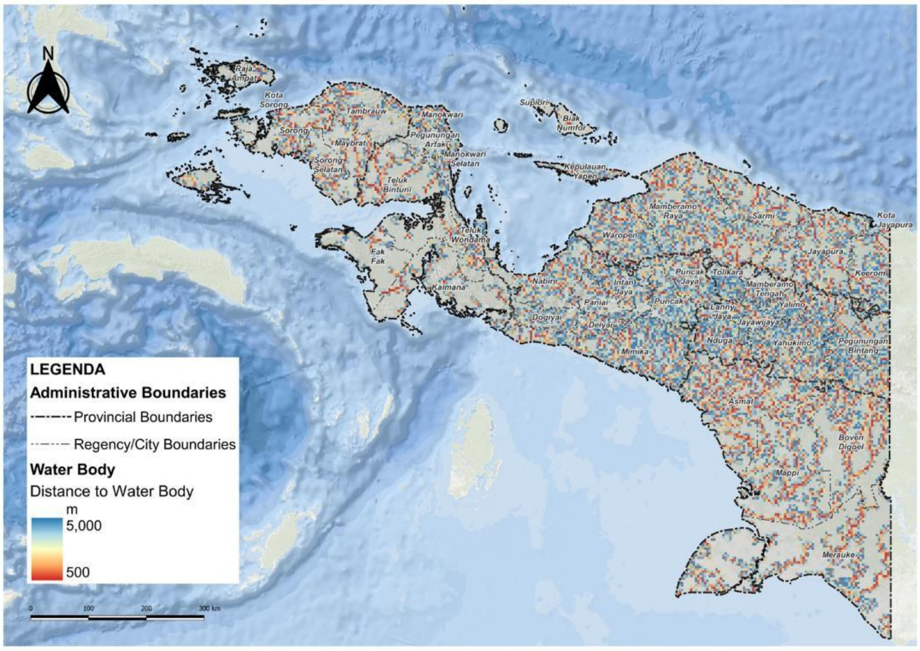


Figure 8. Water body proximity map

The ninth variable was population density, calculated by dividing the population by the area in 2023. The assumption was that higher population density would facilitate the transmission of malaria. However, a study in Chimoi showed a low correlation between malaria cases and population density. Thus, mosquito breeding is often more closely associated with vegetation (Ferrao et al., 2018). Papua is generally a sparsely populated region, with the highest population density being 42 people per square kilometer. The risk assessment was categorized as follows: more than 9,000 people per square kilometer (high risk), between 6,001 and 9,000 people per square kilometer (moderate risk), and less than 6,000 people per square kilometer (low risk) (Figure 10).

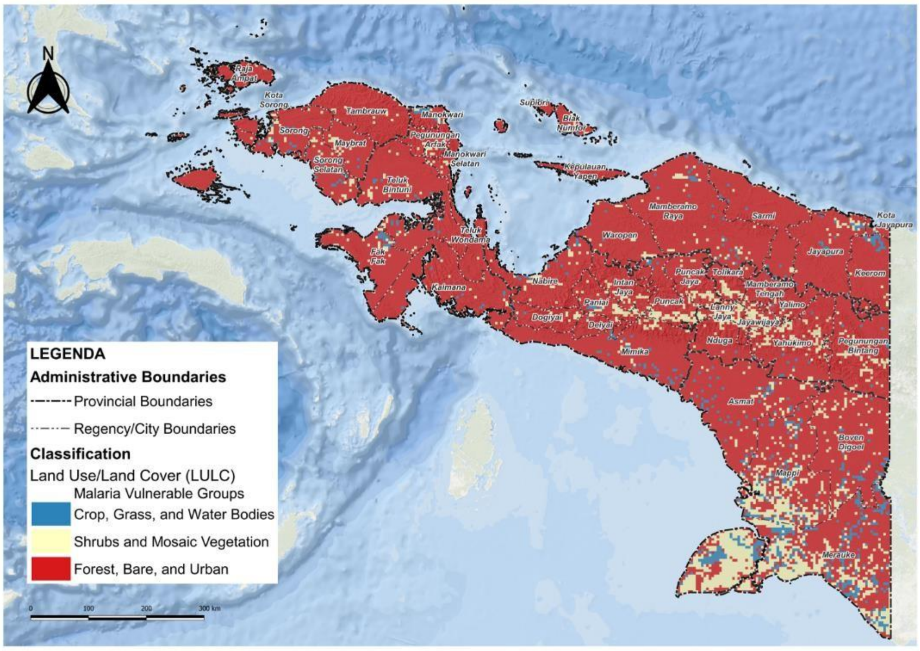


Figure 9. LULC-based malaria vulnerability map

The tenth variable was malaria prevalence, calculated as the number of malaria cases within a year divided by the total population in 2023. Malaria prevalence was used to determine the incidence of malaria and its associated factors. The risk assessment was categorized as follows: greater than 21% (high risk), between 14-21% (moderate risk), and less than 14% (low risk) (Ferrao et al., 2018). Regions with a high malaria prevalence include Keerom Regency (47.14%), Sarmi Regency (41.53%), Mamberamo Raya Regency (41.12%), Mimika Regency (40.93%), Jayapura Regency (27.93%), and Boven Digoel Regency (23.56%) (Figure 11).

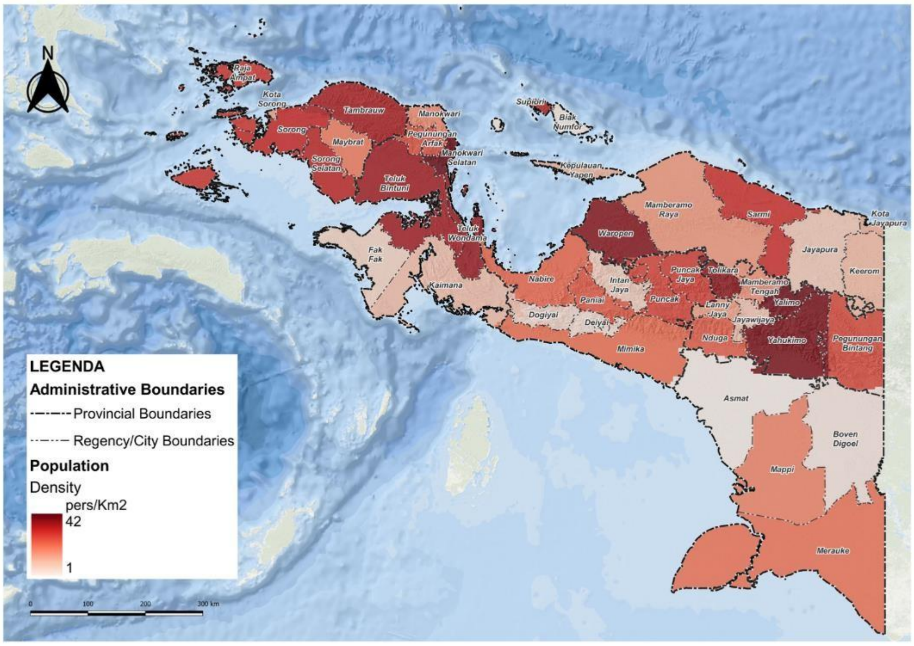


Figure 10. Population density map

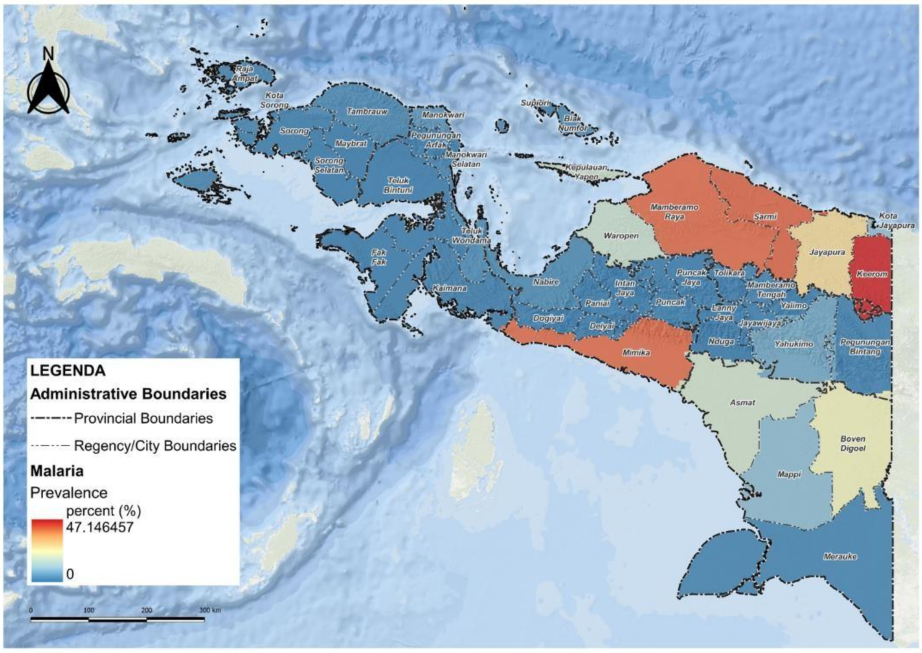


Figure 11. Malaria prevalence map

Following the analysis of individual variables, a reclassification process was performed to standardize the data into three categories. A weighted overlay analysis was then conducted to generate a malaria risk map. The weights assigned to each variable reflected their relative importance based on climatic, clinical, and socio-economic factors specific to Papua. The detailed classification and weighting scheme is presented in Table 1.

Table 1. Weighted overlay analysis

No.	Variable	Influence (%)	Classification	Scoring
1	Annual Average Rainfall	20	903,32-2.488,44 mm	1
			2.488,44-3.413,34 mm	3
			3.413,34-6.410,27 mm	1
2	Slope	8	0-5%	3
			5-15%	2
			> 15%	1
3	Altitude	12	500 m	3
			1.000 m	2
			> 1.000 m	1
4	NDVI	5	-1-0,24	1
			0,24-0,67	2
			0,67-1	3
5	Annual Average Temperature	22	7,97-19,41 °C	1
			19,41-25,02 °C	3
			25,02-35,08 °C	2
6	Road Network Accessibility	3	2.500 m	1
			2.500-5.000 m	2
			5.000-12.500 m	3
7	Water Body Proximity	12	500 m	3
			500-1.500 m	2
			1.500-5.000 m	1
8	LULC-Based Malaria Vulnerability	8	Crop, Grass, Water Bodies	3
			Shrubs and Mosaic Vegetation	2
			Forest, Bare, and Urban	1
9	Population Density	5	1-13 pers/km^2	1
			13-27 pers/km^2	2
			27-42 pers/km^2	3
10	Malaria Prevalence	5	0-15,71	1
			15,71-31,43	2
			31,43-47,14	3

RESULTS AND DISCUSSIONS

Based on the analysis, Papua Province exhibited a range of malaria risk levels, from low to high. Within Papua Province, only Mamberamo Raya Regency was classified as high risk. In Papua Tengah Province, four regencies were categorized as high risk: Nabire Regency, Mimika Regency, Paniai Regency, and Puncak Jaya Regency. Additionally, in Papua Pegunungan Province, five regencies were classified as high risk: Mamberamo Tengah Regency, Nduga Regency, Tolikara Regency, Yalimo Regency, and Yalimo Regency. In Papua Selatan Province, Mappi Regency and Merauke Regency were identified as high-risk areas. Papua Barat Province, on the other hand, did not have any high-risk areas, although most of the province was classified as moderate risk (Figure 12).

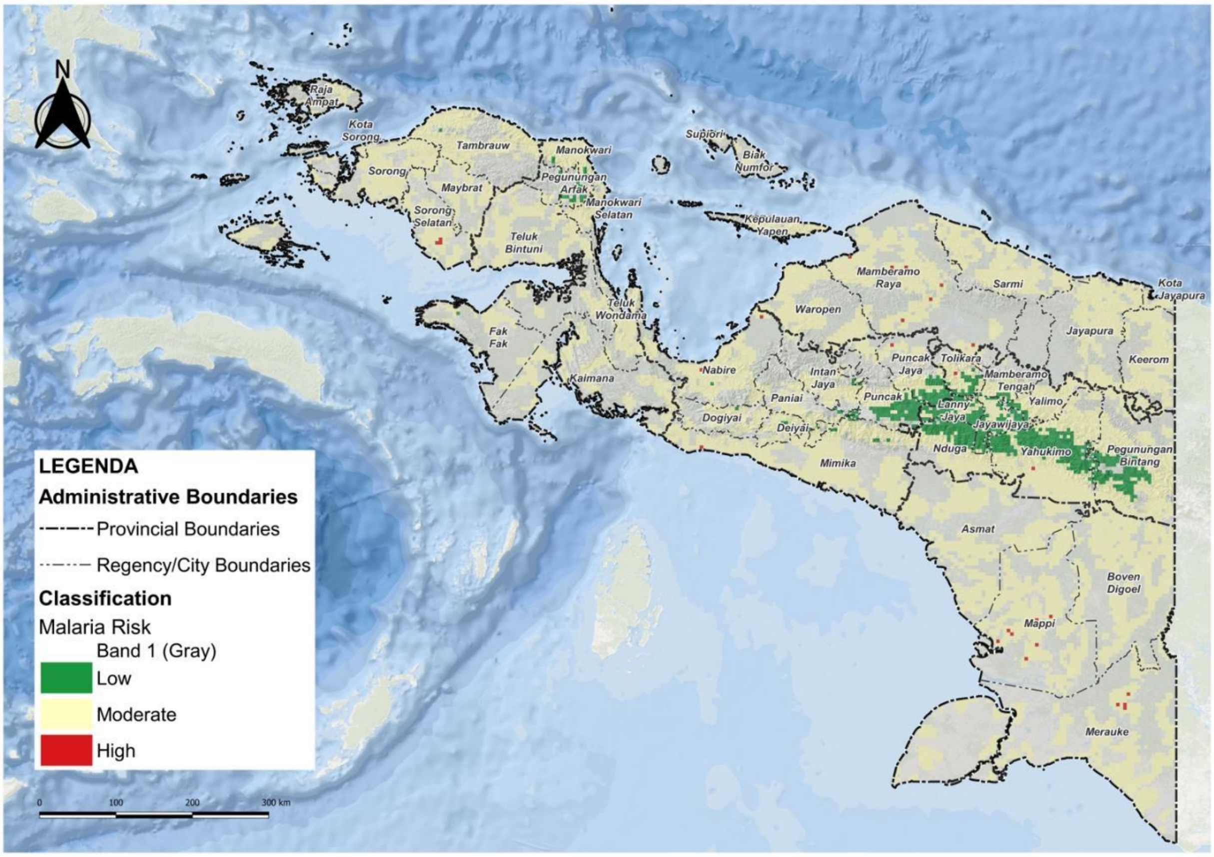
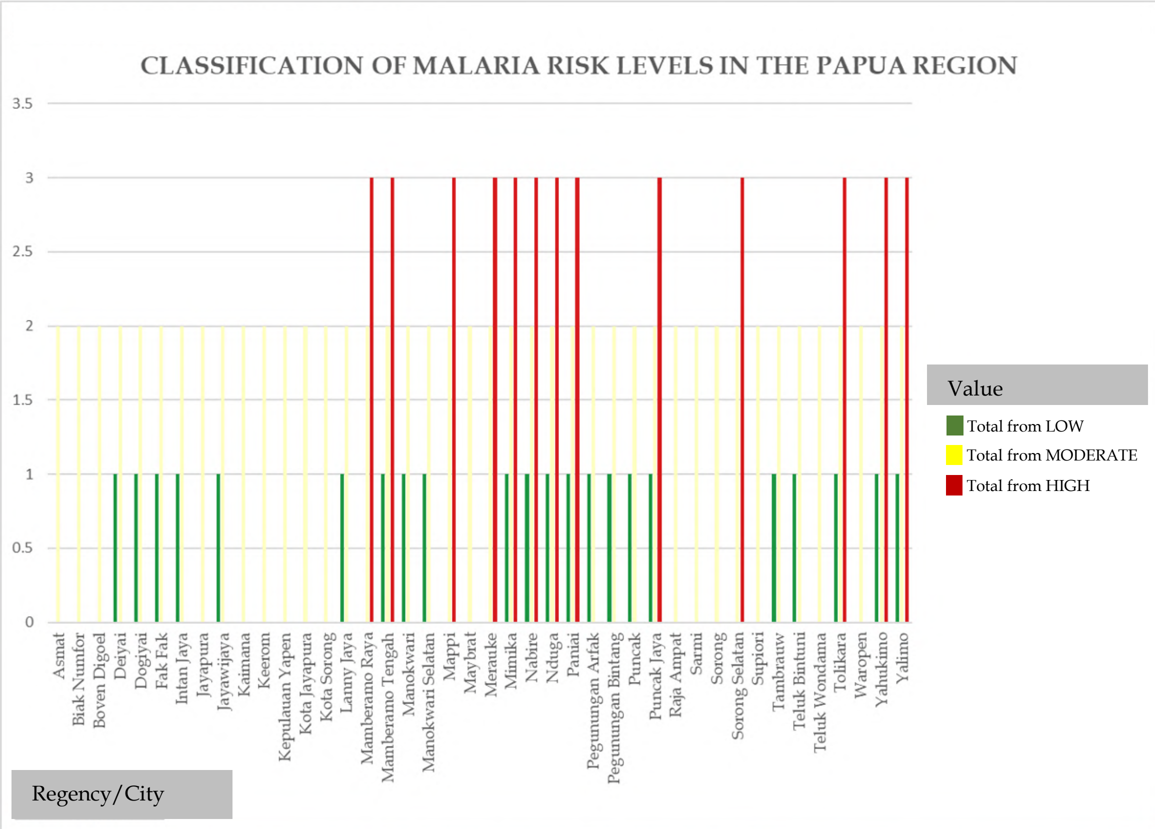


Figure 12. Malaria risk map of Papua

When viewed based on the extent of malaria risk, Mamberamo Raya Regency and Mappi Regency have the highest risk with the largest areas of 165.12 km² and 151.69 km², respectively (Figure 13). This is because both regencies are dominated by water bodies and vegetation, which facilitate the breeding and spread of malaria. Mappi Regency is unique in that it is largely dominated by swampy areas, hence the nickname "a million swamps." This implies that mosquitoes can survive during their incubation period, supported by the low-lying terrain and average temperatures between 28-32°C, allowing for rapid breeding.

As a community living amidst swamps, the Mappi people have unique characteristics and customs, especially considering the tribal structure of Papuan society. The majority of Mappi residents engage in hunting and gathering. This lifestyle means that they spend a significant amount of time outdoors, increasing their risk of mosquito bites and malaria infection. The prevalence of swamps and river systems in Mappi provides ideal breeding grounds for malaria-carrying mosquitoes. Mappi communities typically have dispersed settlements along the banks of these swampy areas, often constructed on stilts. The abundant stagnant water and unsanitary conditions create a perfect ecosystem for mosquito breeding. Additionally, a significant portion of the Mappi population lacks access to clean water, relying solely on rainwater. The low quality and limited access to basic sanitation further compromise the health and hygiene of the community. Limited accessibility to healthcare facilities hinders treatment and potentially contributes to the spread of malaria.

Other regions in Papua with moderate to high malaria risk are priorities for malaria prevention efforts. Malaria transmission is also influenced by human behaviors and practices, such as reluctance to use mosquito nets, non-compliance with antimalarial medication, keeping livestock near homes, nighttime gatherings, open defecation, and hunting and gathering activities that require spending extended periods in the forest. Additionally, substandard housing conditions, including lack of proper structures and basic sanitation, contribute to malaria transmission. Malaria prevention can be achieved through vector control measures such as



REGENCY/CITY	LOW	AREA (Km2)
Deiyai	1	67.02
Dogiyai	1	43.29
Fak Fak	1	21.71
Intan Jaya	1	132.93
Jayawijaya	1	1394.49
Lanny Jaya	1	1654.98
Mamberamo Tengah	1	214.49
Manokwari	1	130.06
Manokwari Selatan	1	8.17
Mimika	1	159.16
Nabire	1	21.65
Nduga	1	1814.91
Paniai	1	151.08
Pegunungan Arfak	1	392.83
Pegunungan Bintang	1	2489.53
Puncak	1	1547.13
Puncak Jaya	1	1046.87
Tambrauw	1	21.74
Teluk Bintuni	1	11.42
Tolikara	1	588.38
Yahukimo	1	4255.81
Yalimo	1	336.24

REGENCY/CITY	MODERATE	AREA (Km2)
Asmat	2	12092.11
Biak Numfor	2	516.15
Boven Digoel	2	12876.47
Deiyai	2	2084.10
Dogiyai	2	2470.42
Fak Fak	2	2047.45
Intan Jaya	2	2391.23
Jayapura	2	6929.05
Jayawijaya	2	975.17
Kaimana	2	5289.93
Keerom	2	5967.27
Kepulauan Yapen	2	1450.82
Kota Jayapura	2	522.85
Kota Sorong	2	158.20
Lanny Jaya	2	562.60
Mamberamo Raya	2	10252.33
Mamberamo Tengah	2	1484.17
Manokwari	2	2168.89
Manokwari Selatan	2	1334.73
Mappi	2	11621.52
Maybrat	2	2879.47
Merauke	2	13973.78
Mimika	2	11916.34
Nabire	2	5878.75
Nduga	2	3352.08
Paniai	2	2336.37
Pegunungan Arfak	2	749.63
Pegunungan Bintang	2	9016.19
Puncak	2	2426.26
Puncak Jaya	2	2259.46
Raja Ampat	2	1994.18
Sarmi	2	6766.71
Sorong	2	5470.29
Sorong Selatan	2	3451.37
Supiori	2	55.13
Tambrauw	2	5904.49
Teluk Bintuni	2	7750.24
Teluk Wondama	2	2331.77
Tolikara	2	1739.86
Waropen	2	5976.40
Yahukimo	2	9382.77
Yalimo	2	2995.71

REGENCY/CITY	HIGH	AREA (Km2)
Mamberamo Raya	3	165.12
Mamberamo Tengah	3	4.06
Mappi	3	151.69
Merauke	3	86.83
Mimika	3	21.63
Nabire	3	43.34
Nduga	3	21.70
Paniai	3	21.66
Puncak Jaya	3	21.71
Sorong Selatan	3	65.20
Tolikara	3	48.17
Yahukimo	3	21.75
Yalimo	3	21.77

Figure 13. Assessment of malaria risk levels and spatial distribution in Papua

indoor residual spraying (IRS) and the use of long-lasting insecticidal nets (LLINs). However, according to the Indonesian Health Survey (2023), several districts in Papua have a lower proportion of LLIN use compared to the national average (38.2%), including Jayapura City (9.7%), Merauke Regency (18.6%), Pegunungan Bintang Regency (20.0%), Nabire Regency (20.6%), Mimika Regency (24.2%), Jayapura Regency (30.9%), Yahukimo Regency (34.7%), Jayawijaya Regency (35.4%), and Boven Digoel Regency (37.2%).

Furthermore, limited accessibility and availability of healthcare facilities have hindered the provision of adequate health services to the people of Papua. Several districts in Papua lack health centers, and accessing hospitals and health centers requires long journeys over poor infrastructure. Additionally, healthcare facilities often have inadequate resources and a shortage of healthcare personnel. Given these challenges, a multi-sectoral approach is essential. Improving access to healthcare services, promoting healthy lifestyles, and empowering communities are crucial steps in preventing malaria transmission and accelerating its elimination in Papua.

CONCLUSION

Malaria is a communicable disease that requires immediate attention, given that 92% of national cases are concentrated in Papua Province. Elimination efforts should be accelerated using geospatial technology to provide a spatial overview of areas with high malaria cases. The malaria risk analysis revealed that approximately 91.77% of the area is at moderate risk and 0.33% is at high risk. Through malaria risk maps, targeted interventions can be implemented in moderate to high-risk areas. Prevention efforts are crucial, including the use of long-lasting insecticidal nets (LLINs), indoor residual spraying during optimal mosquito breeding seasons, and environmental management. Government support is needed to improve access to healthcare services, facilitate early detection and complete treatment of malaria cases, optimize malaria centers, and strengthen multi-sectoral collaboration in malaria control. The private sector can contribute by supporting community empowerment in malaria prevention and control. Enhancing community capacity and literacy regarding malaria risks and promoting healthy lifestyles is essential to accelerate malaria elimination.

It is hoped that future research can continue the analysis to more districts so that the analysis results will be more detailed. The local community participation approach in carrying out district mapping needs to be considered because it knows the conditions and characteristics of the area. The results of risk mapping based on community participation are ideal conditions used to mitigate the spread and support efforts to eliminate malaria. In this way, local governments can carry out preventive measures effectively and efficiently.

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AUTHOR CONTRIBUTIONS

MIM was responsible for variable selection, model development, risk scoring, and map creation, providing a geospatial and territorial perspective. IFPcontributed her expertise in the health domain, while RS focused on the behavioral aspects of the study.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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