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APPLICATION OF REMOTE SENSING AND GIS USING THE ANALYTICAL HIERARCHY PROCESS FOR MALARIA VULNERABILITY MODELING

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A B S T R A C T

Malaria remains a major vector-borne disease and a persistent public health problem in Papua Province, Indonesia, particularly in Jayapura Regency and Jayapura City. This study applies remote sensing and Geographic Information Systems (GIS) integrated with the Analytical Hierarchy Process (AHP) to model malaria vulnerability, while presenting the analysis as a learning case for geospatial-based health studies. Spatial data derived from Landsat 8 OLI, SRTM, CHIRPS, meteorological observations, and official population and malaria records were analyzed using pairwise comparison and weighted overlay techniques. The results indicate that high malaria vulnerability is predominantly associated with lowland and coastal areas characterized by high rainfall, high humidity, and relatively high population density. The resulting vulnerability map shows strong spatial correspondence with reported malaria cases and is easily interpretable. Overall, this study demonstrates that AHP-based remote sensing and GIS analysis not only supports malaria vulnerability assessment but also provides an effective instructional framework for teaching spatial decision-making in environmental and geographic health education.

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INTRODUKTION

Malaria continues to be a major vector-borne disease in tropical regions and remains a persistent public health concern despite decades of control and elimination efforts. In Indonesia, Papua Province consistently reports the highest malaria incidence, with Jayapura Regency and Jayapura City identified as areas where transmission persists over time (World Health Organization, 2021; World Health Organization, 2025). These conditions indicate that conventional control measures require support from spatially informed approaches capable of capturing local environmental variability.

Malaria transmission is strongly shaped by environmental and climatic conditions that regulate mosquito ecology and parasite development. Factors such as rainfall, temperature, elevation, and vegetation structure influence the availability and stability of mosquito breeding habitats as well as vector survival. In the Jayapura region, the coexistence of coastal plains, wetlands, and low-lying settlements alongside hilly and mountainous terrain creates spatial contrasts that lead to uneven malaria vulnerability across relatively short distances. Such heterogeneity underscores the importance of spatial analysis in understanding malaria dynamics at the local scale.

The increasing availability of remotely sensed data and the development of Geographic Information Systems (GIS) have expanded opportunities for spatial analysis of environmentally driven diseases. Remote sensing enables the observation of land surface characteristics in a spatially consistent manner, while GIS supports the integration, analysis, and visualization of multi-criteria spatial information. Previous studies have demonstrated that satellite-derived environmental predictors can effectively capture spatial heterogeneity of malaria risk in tropical regions (Solano-Villarreal et al., 2019), while recent advances emphasize the growing role of satellite observations in strengthening spatial decision support for malaria control and public health planning (Wimberly, 2021). Although these tools have been widely adopted in malaria vulnerability mapping, many studies prioritize model performance and predictive outputs, often providing limited insight into the decision-making logic underlying spatial risk classification. Several studies in Indonesia have demonstrated the usefulness of spatial analysis for identifying malaria-prone areas (Fahmi et al., 2022).

Within this methodological landscape, the Analytical Hierarchy Process (AHP) offers a structured framework for organizing complex environmental information and translating expert judgment into quantitative weights through pairwise comparison (Saati, 1996). The explicit and transparent nature of AHP distinguishes it from purely data-driven approaches and makes it particularly well suited for instructional applications in geography and geospatial science. While previous studies have demonstrated the applicability of AHP for malaria risk mapping (Sarkar et al., 2019), its use as a pedagogical tool that simultaneously supports spatial analysis and geographic health education remains underexplored, especially in regions characterized by strong environmental gradients such as Papua.

Accordingly, this study is situated at the intersection of applied spatial epidemiology and geospatial education. The novelty of this research lies in its emphasis on both analytical clarity and educational relevance by employing an AHP-based malaria vulnerability model derived from remote sensing and secondary data in Jayapura Regency and Jayapura City. Rather than focusing solely on predictive outcomes, this study highlights how multi-criteria spatial modeling can be used to support conceptual understanding of environmental influences on disease distribution within an educational context.

Based on this framework, the study addresses the following research questions:
(1) How do environmental, climatic, and socio-demographic variables contribute to the spatial differentiation of malaria vulnerability in Jayapura Regency and Jayapura City when integrated using the Analytical Hierarchy Process?
(2) Which factors emerge as the most influential in shaping malaria vulnerability, and how are their relative contributions expressed spatially in the resulting model?
(3) In what ways can AHP-based malaria vulnerability modeling be applied as an effective instructional example for teaching remote sensing and GIS in geographic health studies?

Therefore, this study aims to develop a spatial malaria vulnerability model using the Analytical Hierarchy Process integrated with remote sensing and Geographic Information Systems in Jayapura Regency and Jayapura City, while demonstrating its applicability as a practical learning framework in geography and geospatial health education.

RESEARCH METHODS

This study employed a spatial modeling approach integrating remote sensing data and GIS analysis. The study area covered Jayapura Regency and Jayapura City, Papua Province, Indonesia, characterized by diverse environmental conditions ranging from coastal lowlands to hilly and mountainous terrain.

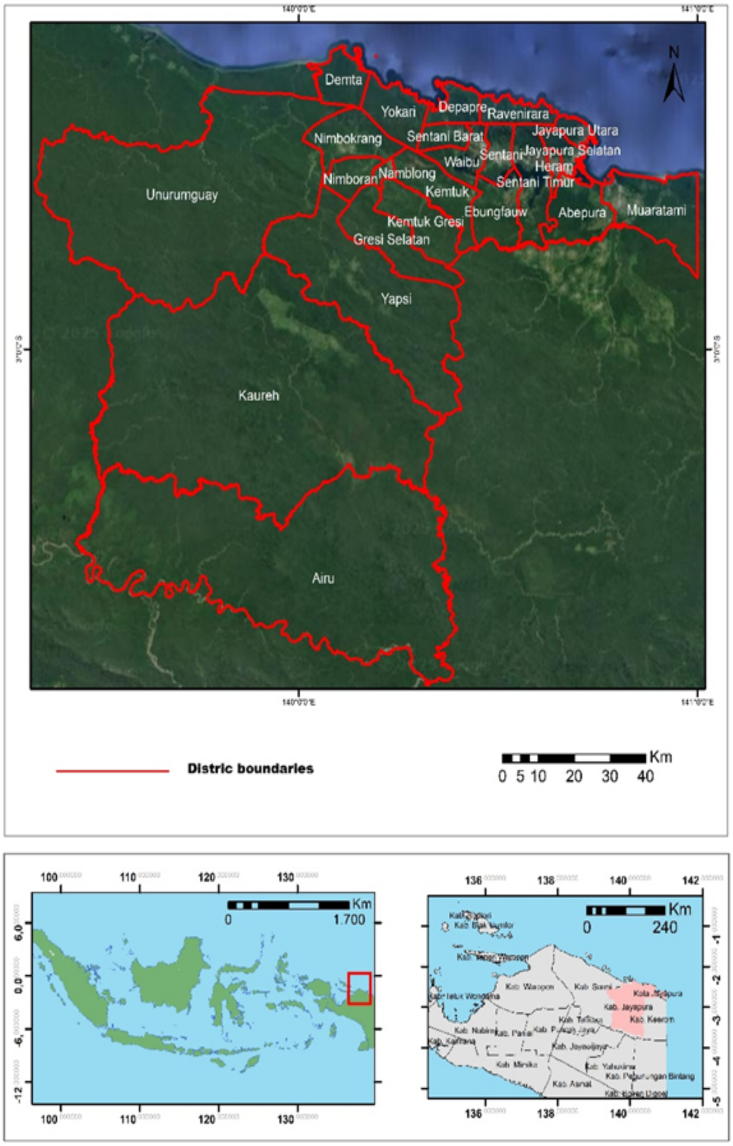

Figure 1. Administrative Boundaries Map

Spatial datasets used in this study included land use, vegetation density (NDVI), land surface temperature (LST), elevation, rainfall, humidity, and population density. Land use, NDVI, and LST were derived from Landsat 8 OLI imagery. Elevation data were obtained from the Shuttle Radar Topography Mission with a spatial resolution of 30 meters, which is widely used for regional-scale environmental analysis. Rainfall data were sourced from satellite-based precipitation products, while humidity data were obtained from meteorological observations and spatially interpolated. Population density and malaria case data were collected from official government institutions.

Table 1. Data and variables used in the AHP-based malaria vulnerability modeling

Variable	Data Source	Spatial Resolution	Role in AHP
Land Use	Landsat 8 OLI	30 m	Environmental factor
Vegetation Density	Landsat 8 OLI	30 m	Environmental factor
Elevation	SRTM DEM	30 m	Environmental factor
Rainfall	CHIRPS	5 km	Climatic factor
Humidity	BMKG meteorological stations	Point data (IDW Interpolation)	Climatic factor
Land Surface Temperature	Landsat 8 OLI	30 m	Climatic factor
Population Density	Statistics Indonesia (BPS)	Administrative unit	Socio-demographic factor
Malaria Cases	Papua Provincial Health Office	Administrative unit	Socio-demographic factor

All spatial datasets were standardized to a common coordinate system and spatial resolution to ensure compatibility during overlay analysis.

The Analytical Hierarchy Process was applied by constructing a hierarchical model consisting of the overall goal (malaria vulnerability), criteria, and sub-criteria. Each criterion was compared pairwise using the Saaty scale to determine its relative importance (Saati, 1996). The consistency of expert judgments was evaluated using the Consistency Ratio, with values below 0.1 indicating acceptable consistency. The final weights were then integrated with spatial layers through weighted overlay analysis in GIS to produce the malaria vulnerability map.

Table 2. Pairwise comparison scale used in the AHP method

Scale Value	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

Table 2 presents the pairwise comparison scale used in the Analytical Hierarchy Process based on Saaty's fundamental scale. This scale was applied to quantify the relative importance between criteria during the pairwise comparison process, allowing subjective expert judgments to be converted into numerical values in a structured and consistent manner.

RESULTS AND DISCUSSION

3.1 Spatial Distribution of Environmental and Socio-Demographic Parameters

To support the malaria vulnerability modeling, this study analyzed the spatial distribution of key environmental and socio-demographic parameters derived from remote sensing and secondary data. The analysis emphasizes how these spatial patterns contribute to malaria transmission dynamics in Jayapura Regency and Jayapura City, particularly through their influence on mosquito breeding suitability, vector survival, and human–vector interaction intensity.

Land Use

Land use and land cover (LULC) patterns strongly influence malaria transmission by shaping ecological conditions favorable for mosquito breeding and determining the intensity of human exposure to vector habitats. The LULC map (Figure 3) shows that forest and natural vegetation dominate most areas of Jayapura Regency, whereas built-up areas and cultivated land are concentrated in Jayapura City and surrounding districts.

This spatial configuration is important because transitional zones between settlements, agricultural land, and natural wetlands create suitable environments for *Anopheles* mosquitoes. In lowland areas, settlements located near swamps, lakes, and slow-moving water bodies may increase the probability of human-vector contact due to the availability of permanent or semi-permanent breeding habitats. In addition, agricultural activities and land clearing can modify local hydrological conditions by creating stagnant water pools that support larval development.

Meanwhile, densely built-up urban areas tend to have lower vegetation cover and fewer natural breeding habitats; however, malaria transmission may still persist in peri-urban zones where settlements expand toward vegetated and wetland environments. This indicates that the spatial interaction between human settlements and water-associated landscapes plays a critical role in determining malaria vulnerability patterns in the study area.

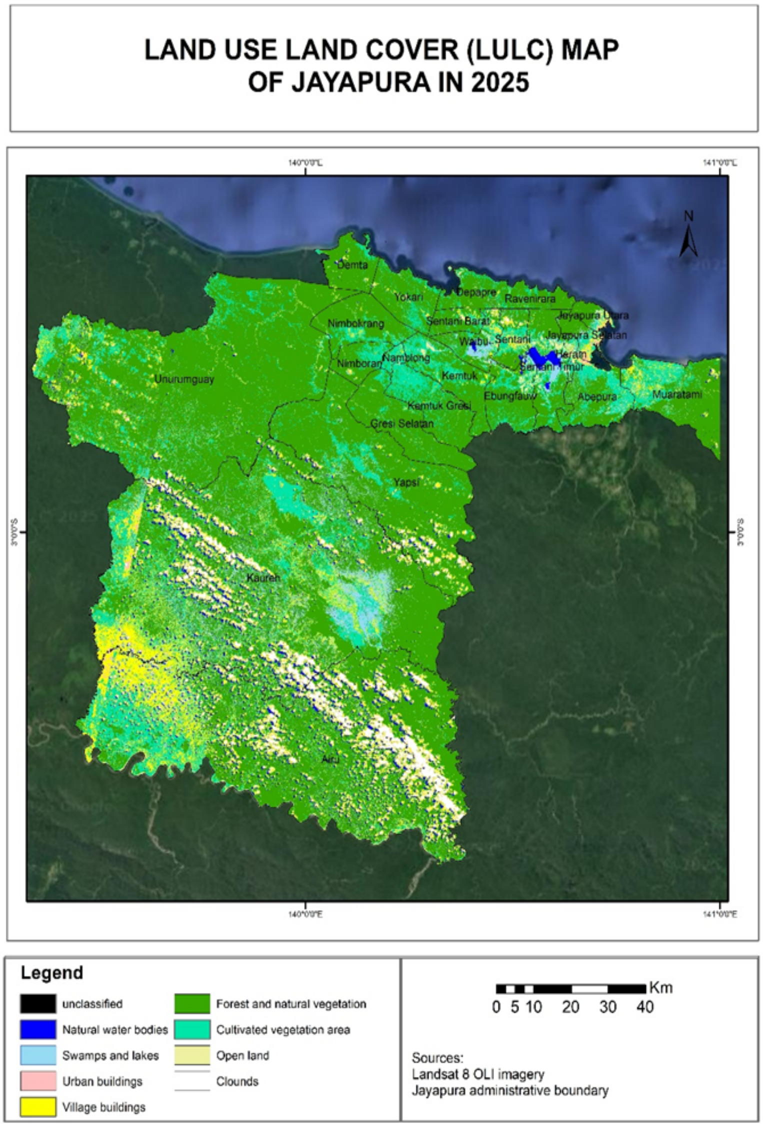

Figure 3. Land Use Land Cover Map

Vegetation Density (NDVI)

Vegetation density influences microclimatic conditions such as shading and moisture retention. The NDVI map (Figure 4) shows that most of the study area is characterized by medium to high vegetation density, particularly in forested and inland regions. Lower NDVI values are observed in urban and built-up areas, indicating reduced vegetation cover that may alter local microclimates and affect mosquito resting behavior.

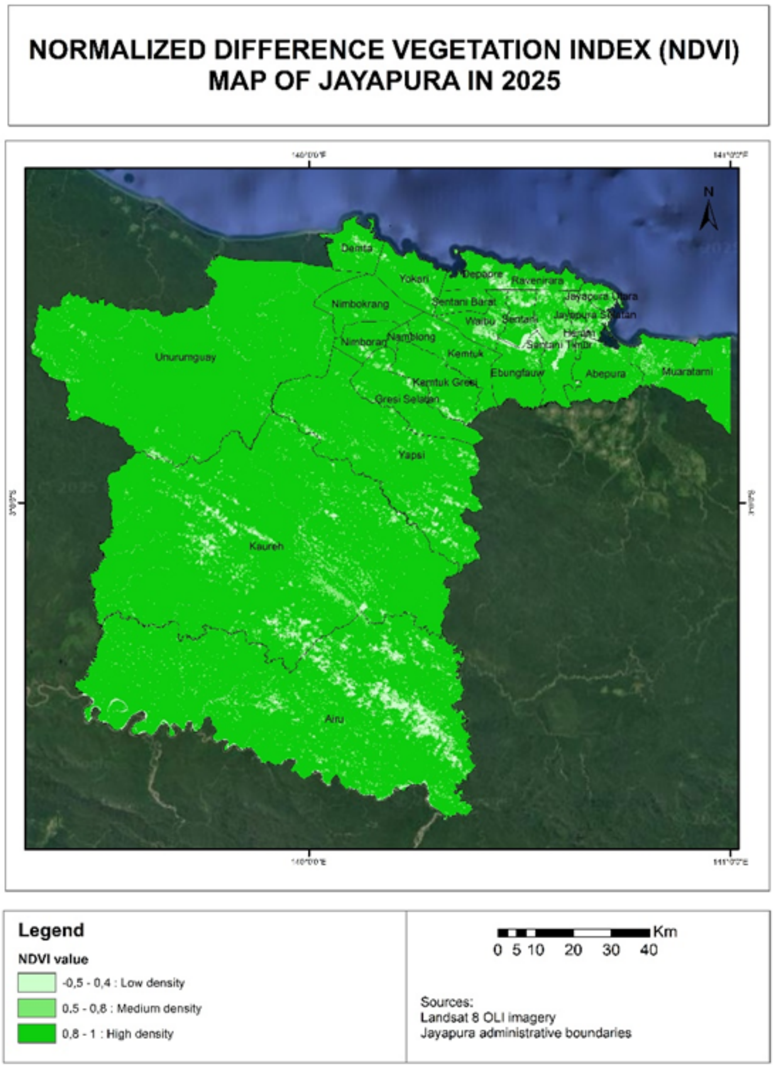

Figure 4. Vegetation Density Map

Elevation

Elevation plays a fundamental role in controlling local climate and hydrological processes that influence malaria transmission. The elevation map (Figure 5) indicates that low-elevation areas (<100 m above sea level) are concentrated along the northern coastal zone and urban districts of Jayapura City, while moderate to high elevations (>500 m) dominate the southern and southwestern parts of Jayapura Regency. The predominance of lowland areas in the northern region increases malaria vulnerability because these areas generally experience higher air temperatures, slower surface drainage, and greater moisture retention, which support the development and survival of *Anopheles* mosquitoes. In contrast, higher elevation zones tend to have cooler temperatures that can reduce mosquito survival rates and slow the development cycle of malaria parasites within the vector. Consequently, the spatial distribution of elevation contributes to the uneven pattern of malaria transmission risk across the study area, with lowland coastal and peri-urban regions exhibiting more favorable environmental conditions for sustained transmission.

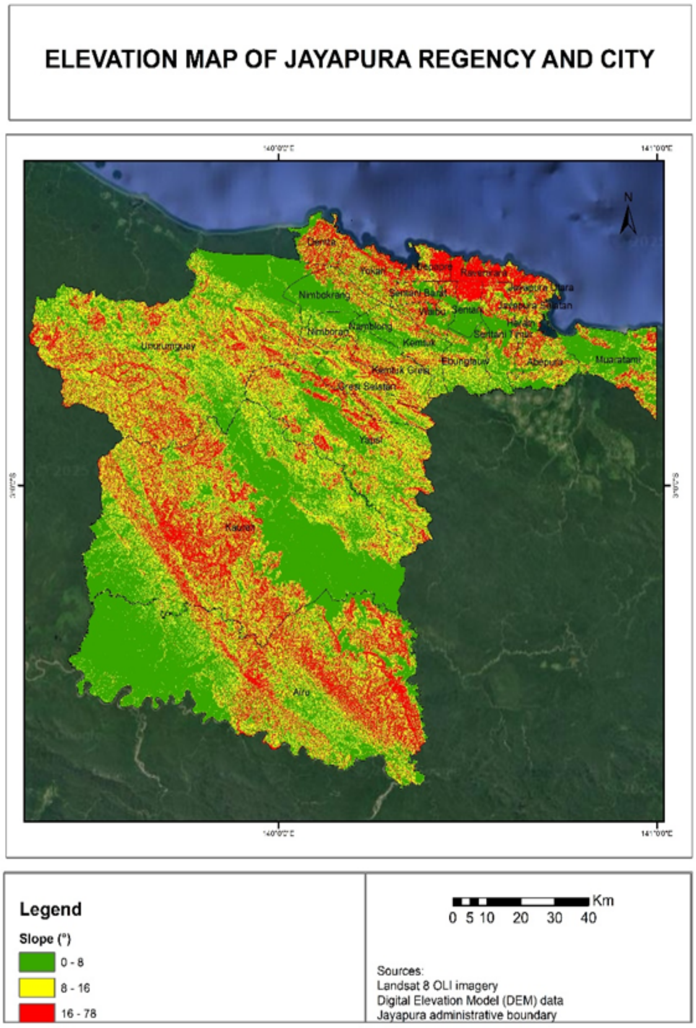

Figure 5. Elevation Map

Rainfall

Rainfall represents a critical climatic factor influencing mosquito breeding site availability. The rainfall map (Figure 6) indicates that moderate to high average monthly rainfall dominates most parts of Jayapura Regency, particularly in southern and western districts such as Kauruh, Airu, and Unurumguay. In contrast, relatively lower rainfall values are observed in northern coastal areas and parts of Jayapura City. This pattern suggests that inland lowland regions provide more favorable hydrological conditions for mosquito breeding compared to coastal urban areas.

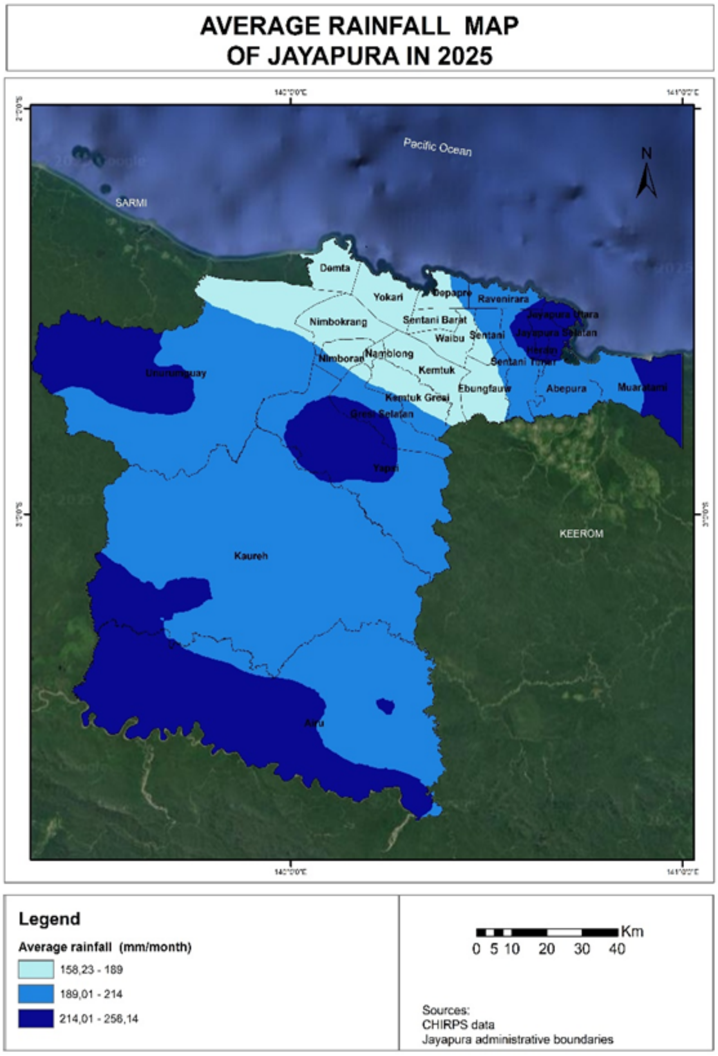

Figure 6. Average rainfall Map

Humidity

Humidity conditions influence mosquito survival and activity duration. As shown in the interpolated humidity map (Figure 7), relatively high humidity levels occur in central and northern districts, including the Sentani area and its surroundings. Lower humidity values are found in some inland and southern regions. The spatial coincidence of high humidity with low-elevation zones reinforces the role of atmospheric moisture in sustaining malaria transmission.

Figure 7. Average Humidity Map

Land Surface Temperature

Surface temperature affects mosquito development and parasite incubation. The land surface temperature map (Figure 8) reveals that higher temperatures are concentrated in lowland and coastal areas, particularly in Jayapura City and adjacent districts, while lower temperatures are associated with higher elevation areas in the southern part of the regency. This spatial pattern reflects the combined influence of elevation and land cover on thermal conditions relevant to malaria risk.

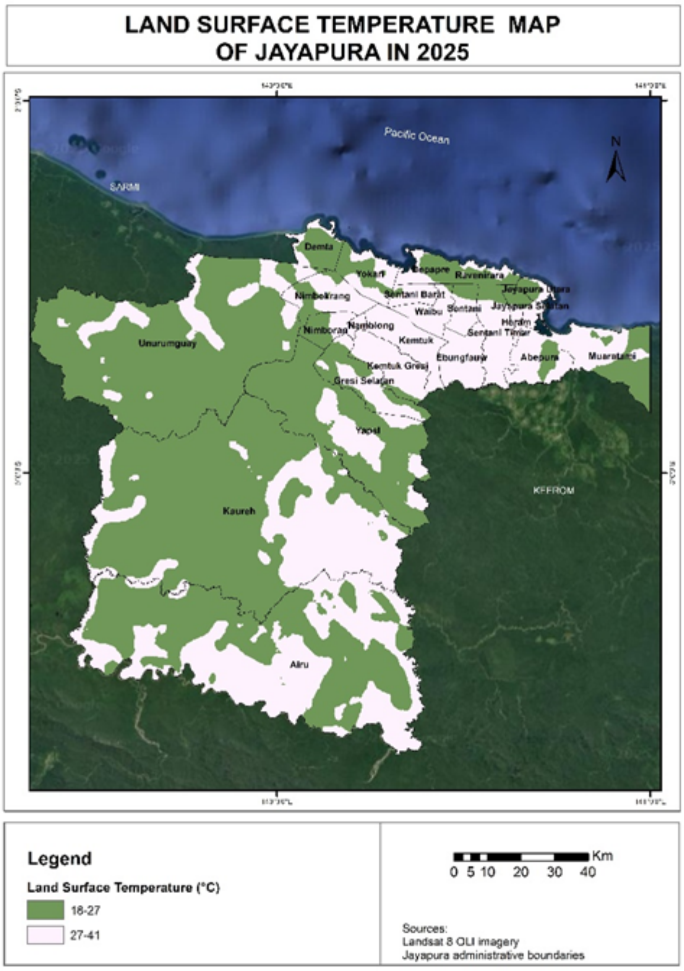

Figure 8. Land Surface Temperature Map

Population Density

Population density reflects the spatial distribution of human exposure to malaria risk. The population density map (Figure 9) demonstrates that high population densities are strongly concentrated in Jayapura City districts, including Jayapura Utara, Jayapura Selatan, Abepura, and Heram. In contrast, most districts in Jayapura Regency exhibit low population density. This uneven distribution highlights that potential malaria exposure is spatially concentrated, even though environmental suitability extends beyond densely populated areas.

Figure 9. Population Density Map

Taken together, these parameter maps indicate that malaria vulnerability in the study area is driven by the convergence of low elevation, high rainfall, high humidity, and favorable thermal conditions, particularly in areas where human settlements are present. These spatial patterns provide the empirical basis for the subsequent AHP-based weighting and malaria vulnerability modeling presented in the following section.

3.2. AHP Weighting Results and Model Consistency

To quantify the relative importance of environmental and socio-demographic factors influencing malaria vulnerability, the Analytical Hierarchy Process was applied to the selected criteria. This section presents the weighting results derived from pairwise comparisons and evaluates the consistency of the decision-making process. The resulting weights provide insight into the dominant factors shaping malaria vulnerability and form the basis for subsequent spatial modeling using a weighted overlay approach.

Table 3. Weights of malaria vulnerability criteria derived from AHP

No.	Criterion	Weight
1	Elevation	0.365
2	Rainfall	0.244
3	Humidity	0.122
4	Land Use	0.091
5	Land Surface Temperature (LST)	0.078
6	Vegetation Density (NDVI)	0.059
7	Population Density	0.040
—	Total	1.000

Source: Data analysis (2025)

Table 4. Results of the AHP consistency test

Parameter	Value
λ max	7.50
Consistency Index (CI)	0.092
Random Index (RI, n = 7)	1.32
Consistency Ratio (CR)	0.0689

Source: Data analysis (2025)

The relative importance of malaria vulnerability criteria derived from the Analytical Hierarchy Process is presented in Table 3. The results indicate that elevation is the most influential factor, with a weight of 0.365 (36.57%). This finding highlights the dominant role of topography in shaping malaria vulnerability in the study area. Low-elevation areas tend to experience warmer temperatures and higher moisture availability, creating favorable conditions for mosquito survival and breeding.

Rainfall is identified as the second most influential criterion, with a weight of 0.244 (24.43%). High rainfall contributes to the formation and persistence of surface water, which serves as potential breeding habitats for *Anopheles* mosquitoes. Humidity, with a weight of 0.122 (12.22%), further supports mosquito longevity and activity, reinforcing the importance of climatic conditions in malaria transmission dynamics.

Land use and land surface temperature show moderate contributions, with weights of 0.091 (9.06%) and 0.078 (7.80%), respectively. These factors reflect the influence of human-induced environmental modification and local thermal conditions on malaria vulnerability. Vegetation density, represented by NDVI, has a relatively lower weight (0.059 or 5.89%), indicating its supporting role in modifying microclimatic conditions rather than acting as a primary driver.

Population density receives the lowest weight (0.040 or 4.04%), suggesting that while human presence is essential for malaria transmission, environmental and climatic factors exert a stronger influence on the spatial pattern of malaria vulnerability in the study area. This result implies that high malaria vulnerability may occur even in sparsely populated areas if environmental conditions are favorable.

The reliability of the AHP weighting process is confirmed by the consistency test results shown in Table 4. The consistency ratio value of 0.0689 is below the acceptable threshold of 0.10, indicating that the pairwise comparison judgments are consistent and the derived weights are reliable for subsequent spatial modeling.

3.3 Spatial Pattern of Malaria Vulnerability

This sub-section presents the spatial pattern of malaria vulnerability derived from the integration of all environmental and socio-demographic criteria using the Analytical Hierarchy Process. The AHP-based spatial model represents the final output of the analysis and synthesizes the combined influence of weighted factors discussed in the previous section. The resulting map provides a comprehensive spatial representation of malaria vulnerability across Jayapura Regency and Jayapura City.

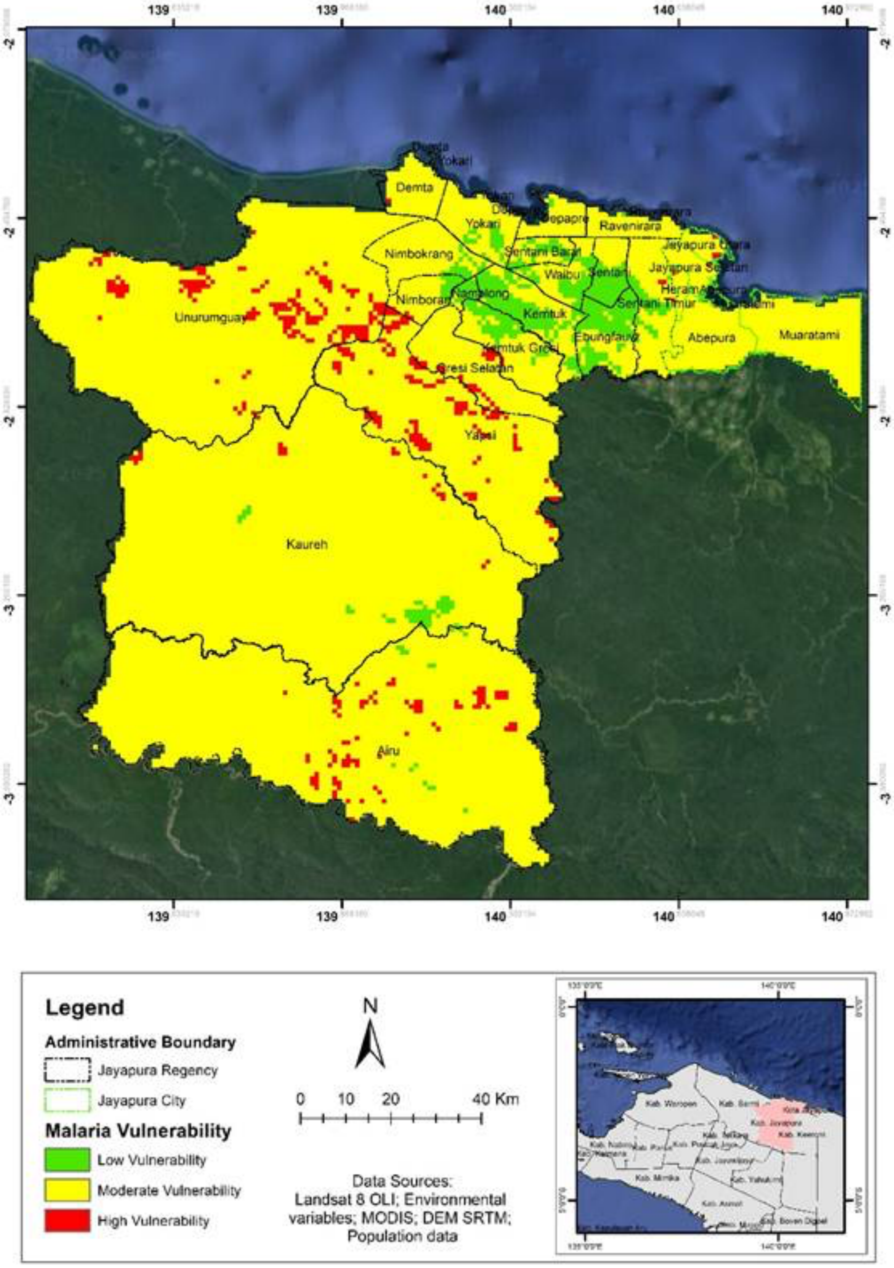

Figure 10. Malaria vulnerability map derived from AHP-based spatial modeling

The integration of all weighted environmental and socio-demographic criteria using the Analytical Hierarchy Process resulted in a malaria vulnerability map classified into low, moderate, and high vulnerability levels (Figure 10). This map represents the final output of the spatial modeling and synthesizes the combined influence of elevation, rainfall, humidity, land surface temperature, land use, vegetation density, and population density.

High vulnerability zones are predominantly concentrated in lowland and coastal areas, particularly in northern parts of Jayapura Regency and several districts of Jayapura City. These areas are characterized by the convergence of low elevation, high rainfall, and high humidity, which collectively support mosquito breeding and malaria transmission. Similar spatial associations between satellite-derived environmental variables and malaria risk have been reported in tropical environments, including the Peruvian Amazon and other malaria-endemic regions (Solano-Villarreal et al., 2019; Machault et al., 2018; Ouedraogo et al., 2018).

Moderate vulnerability zones are generally distributed in transitional areas between coastal lowlands and inland regions, where environmental conditions partially support malaria transmission. In contrast, low vulnerability zones are mainly located in higher elevation areas in the southern part of Jayapura Regency, where steeper terrain and lower moisture availability reduce environmental suitability for mosquito breeding. Comparable elevation-related gradients in malaria vulnerability have also been observed in other malaria-endemic regions with complex topography (Weiss et al., 2019).

The spatial distribution of vulnerability classes demonstrates a clear correspondence with the relative importance of criteria identified in the AHP weighting results (Table 3). The dominance of elevation and rainfall is consistently reflected in the spatial concentration of high vulnerability zones, indicating that the AHP-based model effectively translates weighted criteria into a meaningful spatial representation of malaria vulnerability.

3.4 Discussion and Implications

The findings of this study reinforce the central role of environmental and climatic factors in shaping malaria vulnerability, particularly in tropical regions. The prominence of elevation and rainfall as dominant criteria is consistent with previous studies that highlight the influence of topography and climate on mosquito ecology and malaria transmission dynamics (Gething et al., 2011; Githeko et al., 2017; Midekisa et al., 2015). Recent national-scale malaria risk assessments based on satellite remote sensing in Indonesia also emphasize the importance of environmental gradients in determining malaria risk patterns, although they are often examined at broader spatial scales (Sakti et al., 2025).

However, this study differs from several malaria risk mapping studies that emphasize temperature or vegetation density as the primary drivers of malaria vulnerability (Bai et al., 2019; Bhatnagar et al., 2020). In the context of Jayapura, elevation emerges as a more influential factor, likely due to sharp elevation gradients that strongly regulate local temperature, rainfall distribution, and surface water persistence. This finding suggests that malaria vulnerability models should be adapted to local environmental conditions rather than relying on uniform assumptions, even when satellite-based approaches are applied at national or regional scales (Sakti et al., 2025).

The relatively lower weight assigned to population density also contrasts with studies conducted in highly urbanized settings, where human concentration often plays a more dominant role in malaria risk. In Jayapura, environmental suitability appears to outweigh demographic concentration, indicating that malaria vulnerability may remain high even in sparsely populated areas if ecological conditions are favorable. Similar patterns have been reported in rural and peri-urban malaria-endemic regions, where environmental controls remain dominant despite low population density (Sarkar et al., 2019).

Methodologically, the use of the Analytical Hierarchy Process provides advantages in transparency and interpretability compared to purely data-driven approaches. While machine learning–based models can offer higher spatial resolution and predictive performance, particularly at large spatial extents (Sakti et al., 2025), AHP-based models allow explicit identification of dominant factors and their relative influence, which is valuable for decision support and educational purposes. Comparable applications of multi-criteria decision analysis in malaria risk mapping have been reported in both global and regional studies (Brooker et al., 2018).

Overall, this study aligns with the broader body of malaria vulnerability research while demonstrating context-specific differences driven by local environmental characteristics. These results highlight the importance of integrating remote sensing, GIS, and multi-criteria decision-making approaches to support malaria risk assessment and geographic education, particularly when interpretability and instructional value are prioritized alongside analytical outcomes.

CONCLUSION

This study confirms that the integration of remote sensing, Geographic Information Systems, and the Analytical Hierarchy Process provides an effective and interpretable framework for modeling malaria vulnerability in Jayapura Regency and Jayapura City. By addressing the research questions posed at the outset, the results demonstrate that environmental and climatic factors particularly elevation and rainfall play a dominant role in shaping the spatial differentiation of malaria vulnerability across the study area.

Rather than reiterating empirical findings, this study contributes conceptually by highlighting the value of AHP as an explainable multi-criteria spatial modeling approach that explicitly links environmental processes to disease vulnerability patterns. From a practical perspective, the resulting vulnerability model offers a spatial reference that can support targeted malaria control planning in environmentally heterogeneous regions, while also serving as a structured learning example for applied remote sensing and GIS-based health studies.

Beyond its immediate findings, this study underscores the importance of incorporating local environmental characteristics into malaria vulnerability assessments rather than relying on generalized assumptions. Future research may build upon this framework by integrating data-driven modeling techniques with AHP to enhance spatial detail, incorporating temporal dynamics of malaria transmission, or evaluating the effectiveness of AHP-based models within formal geographic education settings.

BIBLIOGRAFI

Bai, L., Morton, L. C., & Liu, Q. (2019). Climate change and mosquito-borne diseases: A review. *Globalization and Health, 15*(1), 1–11. https://doi.org/10.1186/s12992-019-0503-6

Bhatnagar, S., Gopalan, A., & Jain, S. (2020). GIS-based malaria risk mapping using multi-criteria decision analysis. *Geospatial Health, 15*(1), 1–12. https://doi.org/10.4081/gh.2020.849

Brooker, S. J., Hay, S. I., & Bundy, D. A. P. (2018). Tools from ecology: Useful for evaluating infection risk models? *Trends in Parasitology, 34*(4), 290–300. https://doi.org/10.1016/j.pt.2018.01.006

Fahmi, F., Pasaribu, A. P., Theodora, M., et al. (2022). Spatial analysis to evaluate risk of malaria in Northern Sumatera, Indonesia. *Malaria Journal, 21*(1), 241. https://doi.org/10.1186/s12936-022-04262-y

Gething, P. W., Smith, D. L., Patil, A. P., et al. (2011). Climate change and the global malaria recession. *Nature, 465*(7296), 342–345. https://doi.org/10.1038/nature09098

Liu, Q., Li, Z., Ma, J., et al. (2020). Spatiotemporal patterns of malaria transmission based on remote sensing data. *International Journal of Environmental Research and Public Health, 17*(8), 2811. https://doi.org/10.3390/ijerph17082811

Machault, V., Vignolles, C., Borchi, F., et al. (2018). Remote sensing and malaria risk mapping in tropical environments. *Malaria Journal, 17*(1), 1–13. https://doi.org/10.1186/s12936-018-2360-4

Midekisa, A., Beyene, B., Mihretie, A., et al. (2015). Seasonal associations of climatic drivers and malaria in Ethiopia. *Parasites & Vectors, 8*(1), 1–11. https://doi.org/10.1186/s13071-015-0979-9

Ouedraogo, B., Inoue, Y., & Kambire, H. (2018). Malaria risk mapping using remote sensing and GIS. *Spatial and Spatio-temporal Epidemiology, 26*, 1–10. https://doi.org/10.1016/j.sste.2018.06.002

Rakotoarison, H. A., Rasamimalala, M., Rakotondramanga, J. M., et al. (2020). Remote sensing and multi-criteria evaluation for malaria risk mapping to support indoor residual spraying prioritization in the central highlands of Madagascar. *Remote Sensing, 12*(10), 1585. https://doi.org/10.3390/rs12101585

Sakti, A. D., Surendran, S., & Winarso, H. (2025). Malaria risk assessment and mapping using satellite remote sensing integrated with machine learning across Indonesian provinces. *International Journal of Applied Earth Observation and Geoinformation, 113*, 103027. https://doi.org/10.1016/j.jag.2025.103027

Sarkar, S., Das, S., & Banerjee, S. (2019). Malaria risk map for India based on climate, ecology, and geographical modelling. *Geospatial Health, 14*(1), 747. https://doi.org/10.4081/gh.2019.747

Solano-Villarreal, E., et al. (2019). Malaria risk assessment and mapping using satellite derived environmental predictors in the Peruvian Amazon. *Scientific Reports, 9*, 148. https://doi.org/10.1038/s41598-019-51564-4

Weiss, D. J., Lucas, T. C. D., Nguyen, M., et al. (2019). Mapping the global prevalence of malaria. *Nature, 572*(7768), 1–6. https://doi.org/10.1038/s41586-019-1494-3

Wimberly, M. C. (2021). Satellite observations and malaria: New opportunities for improved spatial decision support. *Progress in Physical Geography, 45*(6), 742–759. https://doi.org/10.1177/03091333211022113

World Health Organization. (2021). World malaria report 2021. *World Health Organization*. https://www.who.int/activities/tracking-malaria

World Health Organization. (2025). Global malaria programme. *World Health Organization*. https://www.who.int/teams/global-malaria-programme