Geo-epidemiological analysis of malaria spots in the Sahelian Drylands of Nigeria

[1,*]Baba-Adamu, M., [1]Babagana-Kyari, M., [1]Mohammed-Taa, U., [1]Adamu, U., [1]Bukar-Lawan T. and [2]Mamman-Adamu, A.

[1]Department of Geography and Environmental Management, Yobe State University, Damaturu, Nigeria
[2]Department of Business Administration, College of Administration, Management and Technology, Potiskum – Yobe State, Nigeria

ABSTRACT

Malaria is a major challenge in the drylands of Nigeria, where transmission is strongly conditioned by climatic instability, environmental fragility and socio-demographic pressures. This study conducted a multi-temporal geo-epidemiological analysis of malaria incidence across Yobe State, aiming to identify climatic–environmental drivers of malaria heterogeneity and delineate spatial hotspots and cool-spots for targeted intervention. The study employed unsupervised machine-learning classification across the three micro-climatic zones – the SaSZ, TZ and SuSZ. Temporal analysis revealed distinct ecological contrasts with the SaSZ displayed weakly increasing but highly erratic incidence patterns ($R^2 = 0.06$), with intermittent peaks in 2016 and 2020. The TZ showed moderate fluctuations ($R^2 = 0.04$) with declines between 2014–2017 followed by resurgence from 2019–2023; while the SuSZ demonstrated a strong rising trend ($R^2 = 0.77$) and the highest burden, with annual incidence ranging from 300–420 cases per 1,000. Seasonal decomposition showed transmission peaks between August and September, following the rainfall-driven breeding cycle. Spatial modelling identified intense hotspots in the SuSZ (indices 0.61–1.0) particularly in Fika, Gadaka and Garin Gambo, while cold-spots (indices <0.10) were concentrated in the SaSZ around Dagona and Azam Kura. NDVI–malaria coupling revealed strong co-variation in wetter zones, with greenness indices consistently aligning with incidence maxima. Population density also correlated positively with malaria intensity, especially in peri-urban and irrigated communities. Generally, the study demonstrated that malaria risk in Yobe State is climate-sensitive, spatially heterogeneous and ecologically stratified. These findings provided an empirical foundation for climate-informed, zone-specific malaria interventions in Nigeria's dryland environments.

Keywords: Geo-epidemiology, Malaria hotspots, Climate variability, Yobe State, Sahel drylands

***Corresponding Author**

Baba-Adamu, M. Department of Geography and Environmental Management, Yobe State University, Damaturu, Nigeria. Email: m.babaadamu001@gmail.com. Telephone Number: +2348065852128.

Citing this article

Baba-Adamu, M., Babagana-Kyari, M., Mohammed-Taa, U., Adamu, U., Bukar-Lawan T. and Mamman-Adamu, A. Geo-Epidemiological Analysis of Malaria Spots in the Sahelian Drylands of Nigeria. KIU J. Health Sci, 2026: 6(2);

Conflict of Interest: None is declared.

INTRODUCTION

Malaria remains one of the most persistent public health challenges in sub-Saharan Africa. Transmission is shaped by interacting climatic, environmental, socio-demographic, and economic determinants. Significant global progress has been made in malaria control. Yet the disease still causes substantial morbidity, mortality, and economic losses across the region. This burden is especially pronounced in ecologically fragile and climate-sensitive settings. The Sahelian drylands of northern Nigeria are a clear example. Here, erratic rainfall, rising temperatures and environmental degradation interact in ways that sustain transmission cycles [21, 24, 32]. Thus, understanding malaria risk in such complex settings requires an approach that captures both space and time. Spatial analysis helps reveal heterogeneity and localized transmission patterns. Temporal analysis helps explain seasonality and longer-term shifts. Together, these approaches can identify persistent hotspots and emerging cool-spots. Cool-spots are areas where transmission is declining, sometimes due to environmental change or behavioural shifts [33]. In parallel, recent advancements in geospatial sciences have strengthened malaria risk modelling. Machine learning, remote sensing and spatial statistics now allow higher-resolution mapping and improved inference on disease heterogeneity and climatic sensitivity [10, 22, 28, 31]. These tools support detailed examination of vector habitat suitability, climate–disease linkages, land-use dynamics and human vulnerability. They also enable more operationally relevant risk stratification. For instance, remote sensing-derived climatic and ecological variables have been used to delineate malaria risk zones and guide targeted interventions [9, 25, 35].

In Nigeria, especially in the northern drylands, evidence is also growing. Studies show that integrating satellite-based temperature and rainfall anomalies with incidence data can improve prediction accuracy and strengthen early-warning capability [3–5, 7, 12].

More so, despite these successes, important methodological limitations persist. Many malaria mapping studies lack adequate temporal depth. Some rely on single-year or short-term datasets. Others omit climatic and ecological variables needed to explain seasonal transmission variability [1, 24]. Some geospatial studies using Landsat imagery and multi-criteria evaluation identify high-risk zones effectively. However, they often lack ground-truth validation. This reduces their utility for operational decision-making [14, 18]. Global malaria trend analyses report an overall decline in incidence. Yet they rarely provide the sub-national granularity needed in heterogeneous environments such as Nigeria's Sahel region [20]. Socio-economic analyses also show how household and demographic characteristics shape malaria risk. However, many do not integrate the environmental and climatic parameters that define malaria ecology in dryland ecosystems [1].

In Nigeria, geospatial malaria studies remain fragmented. Some have linked malaria burden to land-use patterns and population density. Yet several do not integrate key climatic drivers that shape vector survival and parasite development [15, 16]. A multi-criteria study in southern Nigeria provided useful insights. However, it does not incorporate long-term environmental dynamics or validated incidence data needed to calibrate spatial models for Sahelian contexts [17]. Studies in northern Nigeria [3, 4, 7] have begun to close these gaps. They highlighted strong climatic–malaria linkages. They also demonstrate the feasibility of machine-learning methods for predicting temperature- and rainfall-driven malaria trends [3, 4, 7]. Yet, many of these studies focus on climatic trends or spatial patterning alone. Fewer combine multi-temporal ecological and socio-environmental variables within one integrated analytical framework.

Furthermore, malaria transmission is becoming more complex under climate change. Evidence from Mali, Kenya and other settings points to shifting transmission windows and changing hotspot patterns. In these contexts, climate anomalies increasingly influence disease burden [22, 24, 33]. Machine-learning studies are also promising. They can capture non-linear climate–malaria relationships. However, they still face limitations linked to incomplete spatial coverage and weak validation in hyper-arid settings such as the Nigerian Sahel [20, 28]. These gaps highlight the need for a comprehensive, multi-temporal, and ecologically grounded analysis of malaria distribution in Nigeria's drylands. Integrating climatic parameters, environmental conditions, land-cover dynamics, and validated incidence data through advanced statistical models can strengthen understanding of malaria risk transitions. Such an approach can identify persistent hotspots and detect emerging cool-spots. These transitions may reflect ecological restoration, control interventions, or behavioural change [29, 34].

Therefore, this study undertakes a Geo-Epidemiological Analysis of Malaria Spots in the Sahelian Drylands of Nigeria, with a particular focus on Yobe State. It synthesizes climatic, environmental and socio-demographic variables. It applies robust geospatial and statistical methods. In doing so, it generates spatial, temporal, and methodological insights that previous studies in the same setting did not provide. Overall, the study aims to deliver a scientifically grounded evidence base to support adaptive and targeted malaria-control strategies in climatically vulnerable regions of northern Nigeria.

MATERIALS AND METHODS

Study Area

Yobe State is characterized by extensive grasslands interspersed with hardy, drought-tolerant vegetation such as acacia and shrub species. The state lies within a predominantly semi-arid ecological transition where temperatures remain persistently high and rainfall is low and erratic. The climate is defined by a prolonged dry season from approximately October to April and a short rainy season between May and September. These climatic conditions strongly influence water availability, vegetation productivity and broader ecological functioning, which in turn shape agricultural livelihoods and socio-economic vulnerability. Yobe State is also highly sensitive to climate variability, and this has important public health implications because malaria transmission is closely linked to temperature–rainfall regimes that regulate vector breeding habitat availability, mosquito survival and parasite development. This climate sensitivity makes Yobe State a critical setting for examining malaria distribution patterns and their ecological determinants within semi-arid environments.

Data Collection, Zonal Stratification and Analytical Approach

This study used secondary routine malaria surveillance data obtained from the Yobe State Disease Epidemic Repository, complemented by malaria case reports compiled from healthcare facilities across the state. The analysis covered the period 2014–2023, consistent with the temporal window represented in the study's figures. Malaria burden was expressed as incidence per 1,000 population, computed using reported case counts and corresponding population denominators derived from official projections or administrative reporting estimates.

A stratified ecological framework was adopted to enable interpretable comparison across micro-climatic settings within Yobe State. The state was grouped into three zones: the Sahel Savanna Zone (SaSZ), the Transition Zone (TZ) and the Sudan Savanna Zone (SuSZ). Within each zone, one Local Government Area (LGA) was purposively selected to reflect ecological and spatial representativeness: Bade LGA (SaSZ), Damaturu LGA (TZ) and Fika LGA

(SuSZ). This stratification produced a zone-comparative design that is consistent with the visualized outputs, where incidence patterns are reported at zonal level across time and months. The analytical design combined descriptive epidemiological computation with geospatial visualization and time-series summarization. Specifically, the study generated: (i) annual incidence trends by zone (2014–2023); (ii) monthly average incidence profiles by zone (2014–2023) to capture seasonality; (iii) mean annual incidence by zone to summarize long-run burden differences; and (iv) contextual trend comparisons of malaria incidence with NDVI and population density over the same period.

Temporal Trend Modelling and Machine-Learning Tool

Annual malaria incidence time series (2014–2023) were constructed for each ecological zone. To summarize trend behaviour, a linear trend model was fitted to each zonal series, and the goodness-of-fit was reported using R^2 as displayed in the temporal trend figure. The trendlines and R^2 values were generated in Python using the scikit-learn machine-learning library, specifically the LinearRegression estimator (unsupervised trend fitting in the sense of no labelled outcome classification). This ensured reproducible and standardized estimation of slope direction and explanatory strength (variance explained by time). Machine-learning tool used: Python scikit-learn (sklearn.linear_model.LinearRegression) to fit trendlines and compute R^2 for each zone.

Seasonal Pattern Analysis

To characterize malaria seasonality, monthly incidence values were aggregated across all years (2014–2023) to produce monthly average incidence for each zone. This approach reveals the typical seasonal cycle and enables comparison of the timing and magnitude of peaks across zones. The rainy-season period was treated as June–September, consistent with the annotated seasonal window in the visualization. Interpretation focused on onset of seasonal increase, peak months, and decline period, thereby linking malaria dynamics to seasonal rainfall-driven ecological conditions.

Mean Annual Burden and Zone Comparison

To summarize long-run burden differences across zones, a mean annual incidence was computed for each zone as the arithmetic mean of annual incidence values across the 2014–2023 period. These means were presented as a comparative bar chart. The figure also includes descriptive hotspot notes (e.g. Gadaka/Fika; Dahaturi; Gashua/Sabon Gari) to indicate operationally relevant high-burden localities referenced in zones, while maintaining the primary emphasis on zonal burden contrasts.

Contextual Environmental and Demographic Trend Comparisons

To strengthen ecological interpretation, annual malaria incidence trends were compared with time series of NDVI (vegetation greenness proxy) and population density. NDVI was used as a broad proxy for moisture-linked vegetation conditions that can influence malaria ecology by shaping local habitat suitability patterns. Population density was used as a demographic proxy reflecting human concentration and potential transmission-contact structure. These comparisons were presented as descriptive trend plots to examine whether malaria incidence changes co-occur with shifts in vegetation conditions or demographic intensity over the study period. These visual comparisons were interpreted cautiously as contextual evidence rather than causal proof.

Ethical Approval, Data Governance and Confidentiality

Ethical approval for this study was obtained from the Yobe State Primary Healthcare Management Board (YSPHCMB), which granted formal authorization to access and use the malaria surveillance datasets required for analysis. Administrative clearance to use routine public health records was also obtained from the Directors of Public Health in the studied LGAs. As the study relied on secondary routine surveillance data and involved no direct contact with human participants, it was assessed as minimal risk. Ethical oversight was maintained through the YSPHCMB approval process, and the study operated under an appropriate ethical clearance/exemption pathway for secondary anonymized data, as determined by the approving authority. To ensure strong confidentiality and responsible data governance, only de-identified and aggregated records were used. No personal identifiers (names, phone numbers, precise addresses or any directly identifying patient information) were accessed, extracted or reported. Data were used strictly for research purposes, stored securely with restricted access and reported only at approved spatial units (facility/LGA/zone levels as permitted), ensuring anonymity, confidentiality and compliance with data governance obligations.

RESULTS AND DISCUSSIONS

Temporal Trends of Malaria Incidence

The temporal behaviour of malaria incidence in Yobe State displayed clear ecological contrasts. It also highlighted how climate variability, hydrological conditions and intervention continuity interact to sustain or suppress malaria transmission. Annual incidence was treated as the outcome series for each zone. A simple linear trend line was fitted to each annual time series. The reported R^2 values quantify the proportion of variation in annual incidence explained by the passage of time. In other words, a high R^2 indicates a strong, consistent time-related trend. A low R^2 indicates that incidence is dominated by irregular shocks and year-specific drivers rather than steady long-term change.

In the Sahelian Savannah Zone (SaSZ), malaria incidence fluctuated with irregular peaks, notably in 2016 and 2020, and lacked a strong linear trend ($R^2 = 0.06$). The weak association implied that year-to-year changes are shaped not by time progression but by external climatic and environmental perturbations. This observation is consistent with studies across Sahelian drylands. In those settings, rainfall anomalies, temperature fluctuations and ecological shocks are major determinants of transmission volatility [2, 26]. Similar inconsistencies in temporal trends have been documented in climate-malaria analyses from sub-Saharan Africa. Transmission patterns there vary in response to episodic climatic triggers rather than smooth long-term progressions [21,27].

In the Transitional Zone (TZ), malaria incidence declined between 2014 and 2017. This suggested short-term effectiveness of integrated malaria interventions. However, incidence rose again from 2019 to 2023. This oscillation echoed the earlier findings from African drylands. Those studies show resurgence following disruptions in malaria control or adverse environmental events [21]. The low R^2 value (0.04) for the TZ reinforced that transmission outcomes depend heavily on intervention stability and ecological conditions. This aligned with spatial epidemiological assessments. In such assessments, temporary intervention gains are often reversed when coverage declines [13,20].

The Sudan Savannah Zone (SuSZ) exhibited a distinctly different temporal pattern. It demonstrated a strong increasing trend over the decade ($R^2 = 0.77$). This sustained rise corresponds with evidence that wetter ecological belts experience persistent malaria transmission. This persistence is supported by higher humidity and longer rainy seasons that improve vector survival [12,27]. The dramatic 2020 peak reflected outbreak signalled observed in climate-sensitive malaria studies conducted in the Sahel corridor [15]. This reinforced that even small climatic deviations can accelerate malaria incidence. Across zones, the temporal analysis shows that malaria in Yobe State is driven predominantly by climate and ecological variability rather than linear annual change. This corroborated the broader literature on climate-linked malaria dynamics in Africa [2,26].

Seasonality of Malaria Incidence

The seasonal profile of malaria incidence (Figure 2) revealed a classic Sahelian pattern. Transmission intensified from June, peaked between August and September, and declined rapidly from October onward. Monthly values were treated as a seasonal cycle. They were averaged across years to produce monthly climatologies for each zone. This procedure reduced short-term noise and highlighted the "typical" within-year malaria rhythm. This pattern aligned with established evidence that rainfall controls mosquito breeding by creating temporary stagnant pools. These pools trigger a predictable seasonal rise in malaria cases [26]. The observed one-month lag between peak rainfall and peak malaria incidence reflects two biological processes. The first is mosquito development from larva to adult. The second is the extrinsic incubation period of Plasmodium inside the mosquito. This lag structure is widely reported in climate-malaria studies across Africa [2,27].

Seasonal variations were most pronounced in the SuSZ. Here, longer rainy seasons, agricultural irrigation and floodplain hydrology sustain vector breeding beyond the natural rainy period. This effect is similarly noted in semi-arid Nigerian agricultural landscapes [12]. The TZ showed moderate amplitude. The SaSZ exhibited short-lived but sharp seasonal spikes. This is consistent with a highly arid climate, where ephemeral pools offer temporary but productive breeding sites. These findings aligned with climate-health research. That literature shows Sahel malaria is tightly synchronized with rainfall timing and intensity [26,27].

The implications for public health programming are significant. Seasonal peaks indicated that the interventions must be time-bound. Because global recommendations emphasised deploying ITNs, strengthening surveillance and conducting Seasonal Malaria Chemoprevention (SMC) before the onset of rains [24]. Predictive modelling studies also show that integrating NiMet rainfall forecasts into early-warning systems can improve preparedness [2]. The seasonality patterns therefore reinforced climate sensitivity and the need for climate-informed intervention planning.

Spatial Distribution and Zone-Level Variation of Malaria Burden

Spatial modelling (Figure 3) revealed strong geographical disparities in malaria burden across Yobe State. The patterns reflect ecological gradients and hydrological conditions. Here, the term **hotspot "index"** refers to a standardized intensity score used to rank relative malaria burden across locations on a comparable scale. In practical terms, the index represents a rescaled burden measure (e.g. normalized to range from 0 to 1). Values closer to 1 represent the highest observed burden category. Values close to 0 represent the lowest observed burden category. This makes spatial comparisons interpretable even when raw incidence values differ widely across zones.

The SuSZ contained the highest-intensity hotspots (indices 0.61–1.0), clustering around Gadaka, Fika and Garin Gambo. These areas coincide with floodplains and irrigation corridors. Such settings sustain more persistent breeding habitats. This is consistent with spatial malaria studies in northern Nigeria that identify irrigated agricultural landscapes as high-risk zones [12]. Similar hydrology-driven hotspot formation has also been documented in broader African wetland systems [27].

The TZ displayed moderate but spatially concentrated hotspots, particularly in peri-urban communities such as Dahaturi and Kukareta. These hotspots are consistent with environments where poor drainage and surface water accumulation create persistent larval habitats. This reinforced the earlier findings that peri-urban environments with inadequate sanitation infrastructure contribute significantly to malaria persistence [9,17]. Conversely, coldspots detected in Gabai and Gambir (indices <0.11) suggested the that dryness, sparse vegetation and possibly improved access to health services suppress transmission in these localities. Methodologically, these coldspots corresponded to the lowest segment of the standardized burden scale, meaning areas that consistently fall in the lowest observed burden class.

The SaSZ exhibited smaller hotspots near Gashua and Sabon Gari. These are mainly along seasonal floodplains of the Komadugu–Yobe river system. This demonstrated that even arid belts experience transmission intensification where surface water accumulates. This pattern is consistent with hotspot identification research in dryland East Africa [8,27]. Overall, the spatial heterogeneity underscores the need for **micro-stratified interventions** rather than uniform programming. The WHO recommends tailoring interventions to localized epidemiological risk, especially in settings with steep ecological gradients [24]. The varied patterns in Yobe State show that uniform interventions are insufficient. They also show that geospatial intelligence should inform intervention targeting to maximize impact.

Spatio-Temporal Variations Across Climatic Zones

Table 1 further illustrated how climatic zones shape malaria incidence patterns. The SaSZ exhibited the lowest annual incidence (160–230 per 1,000). This reflects brief rainfall, limited humidity and shorter mosquito survival. It matches the typical pattern of arid drylands where transmission is short-lived and tightly seasonal [26]. The TZ showed intermediate incidence (210–320 per 1,000). This corresponds with moderate rainfall and temporary breeding habitats. By contrast, the SuSZ demonstrated the highest incidence range (300–420 per 1,000). It also exhibited a longer transmission season from May to October. This gradient follows established climate–malaria relationships. Wetter zones consistently record higher malaria burden because vector ecological conditions are more optimal [12,25,27].

Collectively, these patterns confirmed that malaria distribution in Yobe State is driven by a north–south ecological gradient. Rainfall duration, humidity and land-cover transitions shape transmission intensity and duration. These findings mirror climate-malaria assessments across sub-Saharan Africa. That literature emphasizes the dominant role of climate and hydrology in defining malaria risk [2,26,27].

NDVI–Malaria Relationships

The NDVI–malaria relationship shown in Figure 4 indicated that the higher vegetation greenness generally corresponds to higher malaria incidence. This is most apparent in the SuSZ, where NDVI values are consistently higher than those of the Sahelian belt. Methodologically, NDVI serves as a remote-sensing proxy for vegetation productivity and, indirectly, surface moisture and ecological suitability. These conditions can support Anopheles breeding and survival, especially where greenness reflects rainfall and standing water persistence. This interpretation is consistent with evidence that NDVI is a useful proxy for moisture-linked habitat suitability in tropical and Sahelian settings [2,11,26,27].

The curve shows synchronous or slightly lagged peaks of NDVI and malaria incidence. This pattern echoed findings from previous studies [8,11,27]. The weaker association in the SaSZ is also expected. In this zone, NDVI values remain low and highly variable, reflecting sparse vegetation and short-lived moisture availability. This is consistent with findings from some studies [20,25,26]. The NDVI–malaria co-variation findings also aligned with recent geospatial and climate–malaria work that highlighted the importance of seasonal vegetation and hydrological conditions in shaping both hotspots and cool-spots. Studies [3,5–7,12] show that increased vegetation and surface moisture are associated with higher malaria incidence. The findings here are consistent with those patterns. This is because investigations [2,13,24,26] show that early warning indices combining rainfall, temperature and greenness can anticipate seasonal surges in malaria burden across sub-Saharan Africa. Thus, the results reinforced that malaria risk in Yobe State is coupled to environmental greenness and water availability. Zones with persistently higher NDVI therefore require more intensive and spatially targeted control.

Population Density–Malaria Relationships

Figure 5 highlighted a tendency for higher malaria incidence in more densely populated settlements than in sparsely populated areas. Methodologically, population density is treated here as a contextual spatial metric capturing human concentration and the likelihood of intensified human–vector contact in settings where drainage and housing quality may be inadequate. This pattern is consistent with studies showing that higher population concentration, informal housing and poor drainage create high-contact environments that amplify malaria transmission even under similar macro-climatic conditions [9,11,15,17]. Studies of under-five malaria in multi-country and Nigerian settings also show that dense, socio-economically vulnerable communities face higher risk. This is linked to crowding, limited access to preventive tools and increased human–vector contact [1,10,25].

These impliedly mean that places with intermediate to high population densities appeared as consistent incidence peaks. This echoed findings from Rivers and Jigawa States where settlement structure and mobility intensify malaria heterogeneity [9,16,25]. At the same time, Figure 5 also suggested divergence in some places. Some relatively dense centres display lower incidence than expected. This aligned with findings showing that improved housing, stronger health systems and higher intervention coverage can weaken a simple positive density–malaria relationship [16,19,21,27]. Machine-learning and spatial modelling studies further show that the strongest hotspots tend to emerge where three conditions overlap: dense population, environmental suitability and gaps in control coverage. They do not emerge uniformly across all dense locations [14,18–20,23].

In this respect, Figure 5 is valuable because it shows socio-demographic modulation of environmental risk. Densely populated irrigation belts, peri-urban floodplains and market towns appear as more persistent hotspots. Sparsely populated, arid Sahelian areas remain relative cool-spots even when NDVI briefly rises. Taken together, Figures 4 and 5 provided a coherent interpretation aligned with the wider literature. Malaria risk in Yobe State is shaped by the intersection of climatic–environmental suitability and socio-demographic concentration. This reinforced the need for micro-stratified, climate-aware and equity-focused control strategies [3,5,7,11,14,21,24–27].

CONCLUSION

This study provided a scientifically grounded, spatially nuanced and temporally detailed account of malaria epidemiology in the Sahelian drylands of Nigeria. It shows that malaria transmission in Yobe State is shaped by an interacting set of ecological, climatic and socio-demographic drivers. The zonal analyses demonstrated that malaria risk is not uniformly distributed across the state. Instead, it varied sharply along ecological boundaries. The SuSZ consistently emerged as the most malaria-intense setting. This pattern is plausibly linked to higher rainfall totals, prolonged wet seasons and hydrological systems that sustain stable breeding habitats. In contrast, the SaSZ, although generally arid, exhibited episodic and spatially fragmented hotspots. These appear to be associated with temporary water bodies, population concentration and micro-environmental modifications. The TZ showed intermediate but fluctuating patterns. This highlights malaria sensitivity to rainfall variability and likely variation in intervention continuity and service access.

The temporal analyses further show that malaria dynamics in Yobe State are climate-sensitive but not strictly time-linear. Incidence displays pronounced seasonal peaks, typically around August–September, which coincide with the rainy season and the biological development cycles of Anopheles vectors and Plasmodium parasites. The seasonal signature is strongest in the SuSZ, moderate in the TZ and shorter-lived in the SaSZ. Together, the results indicate that hydrology, land-use conditions and settlement morphology shape where and when transmission intensifies. In particular, elevated burden along irrigation corridors, floodplains and peri-urban settlements is consistent with environments where surface water persistence and drainage limitations can support breeding habitats.

These findings have important policy implications. They suggest that blanket, uniform malaria strategies may be inefficient in ecologically diverse dryland settings. Instead, Yobe State would likely benefit from an adaptive, geographically stratified malaria-control framework that combines climate-informed preparedness, seasonal timing of interventions and localized risk prioritization. Such an approach would strengthen planning for surveillance, case management and prevention in zones and localities where transmission pressure is consistently higher or seasonally amplified.

At the same time, it is important to interpret these policy implications in light of methodological limitations. First, the analysis is based on secondary routine surveillance data, which may be affected by under-reporting, changes in testing practices, reporting completeness or health service access over time. Second, the zonal comparison relied on ecological aggregation and selected representative contexts, which can mask finer-scale heterogeneity in zones and limit the precision of hotspot generalization beyond the mapped settings. Third, the trend modelling reported here is descriptive and does not, by itself, establish causality between climatic proxies (e.g. NDVI) or population density and malaria incidence. These relationships may be influenced by unmeasured confounders such as intervention coverage, housing quality, migration and local water management practices. Finally, the hotspot indications presented are operationally informative but would be strengthened by formal hotspot statistics and independent validation where data allow.

In these constraints, the study still advances geo-epidemiological understanding by jointly presenting temporal trends, seasonal patterns and spatial contrasts across ecological zones. It provided a structured basis for prioritizing surveillance and interventions by season and by geography. The identification of persistent high-burden settings and potential emerging coolspots also offers a pathway toward more targeted malaria management aligned with global strategies for resilient health systems under accelerating climate change.

REFERENCES

[1] Anjorin, S., Okolie, E. and Yaya, S. (2023). Malaria profile and socioeconomic predictors among under-five children: an analysis of 11 sub-Saharan African countries. *Malaria Journal*, *22*(1), 55. DOI: https://doi.org/10.1186/s12936-023-04484-8

[2] Ayanlade, A., Nwayor, I. J., Sergi, C., Ayanlade, O. S., Di Carlo, P., Jeje, O. D. and Jegede, M. O. (2020). Early warning climate indices for malaria and meningitis in tropical ecological zones. *Scientific Reports, 10*, 14303. DOI: https://doi.org/10.1038/s41598-020-71094-8

[3] Baba-Adamu, M., Ngamdu, M.B., Adamu, U. and Abubakar-Jajere, A. (2024). Assessing the climatic drivers of malaria transmission in Yobe State, Nigeria. *Gombe Journal of Geography and Environmental*

Studies (GOJGES), *4*(2), 114 – 124. https://www.gojgesjournal.com/vol04is02.php

[4] Baba-Adamu, M., Ngamdu, M.B., Adamu, U. and Abubakar-Jajere, A. (2025). Exploring the nexus between climatic factors and malaria risks in the Nigerian Sahel. *Journal of Applied Sciences, Information and Computing (JASIC), 6*(1), 131 – 137.

[5] Baba-Adamu, M., Babagana-Kyari, M., Bukar Ngamdu, M., Adamu, U. and Abubakar Jajere, A. (2025). Malaria risk mapping in the Sahel Region of Nigeria: A geospatial approach. *Sustinere: Journal of Environment and Sustainability*, *9*(2), 198–211. DOI: https://doi.org/10.22515/sustinere.jes.v9i2.530

[6] Baba-Adamu, M., Ngamdu, M.B., Adamu, U. and Jajere, A. A. (2025). Machine Learning Analyses of Climate Variability Trends and Malaria Transmission Dynamics in Yobe State, Nigeria. *UMYU Scientifica, 4(2)*: 258 – 269. DOI: https://doi.org/10.56919/usci.2542.026

[7] Burga, H. A. and Mohammed, H. I. (2025). Geospatial assessment of malaria health risk in Kaduna North Local Government Area of Kaduna State. *UMYU Scientifica*, *4*(1), 280-296. DOI: https://doi.org/10.56919/usci.2541.028

[8] Diriba, D., Karuppannan, S., Regasa, T. and Kasahun, M. (2024). Spatial analysis and mapping of malaria risk areas using geospatial technology in the case of Nekemte City, western Ethiopia. *International Journal of Health Geographics, 23*, 27. DOI: https://doi.org/10.1186/s12942-024-00386-3

[9] Egbom, S. E., Nduka, F. O. and Nzeako, S. O. (2022). Point prevalence mapping of malaria infection in Rivers State, Nigeria. *Tanzania Journal of Health Research*, *23*, 1 – 11. DOI: https://doi.org/10.4314/thrb.v23i4.7

[10] Eneanya, O. A., Reimer, L. J., Fischer, P. U. and Weil, G. J. (2023). Geospatial modelling of lymphatic filariasis and malaria co-endemicity in Nigeria. *International Health, 15:* 566–572. DOI: https://doi.org/10.1093/inthealth/ihad029

[11] Feng, J., Xiao, H., Xia, Z., Zhang, L. and Xiao, N. (2015). Analysis of Malaria Epidemiological Characteristics in the People's Republic of China, 2004-2013. *American Journal of Tropical Medicine and Hygiene, 93(2)*: 293 – 9. DOI: 10.4269/ajtmh.14-0733

[12] Garba, L.C., Houmsou, R.S., Akwa, V.Y., Wama, B.E., Ikpa, F.T., Kela, S.L. and Amuta, E.U. (2023). Spatial features of malaria in the lowland and nearby highland areas of Taraba State, Nigeria. *Scientific African*, *22,* e01969. DOI: https://doi.org/10.1016/j.sciaf.2023.e01969

[13] Gebre, S.L., Temam, N. and Regassa, A. (2020). Spatial Analysis and Mapping of Malaria Risk Areas Using Multi-Criteria Decision Making in Didessa District, South West Ethiopia. *Cogent Environmental Science, 6*(1): 1860451. DOI: 10.1080/23311843.2020.1860451

[14] Jinad, S., Kama, M.O., Baba-Adamu, M., Ikegwu, A.C. and Machete, O. (2025). Analysis of malaria and climate in Damaturu City of Nigeria using predictive supervised learning. *Discover Sustainability*, 6:1239. DOI: https://doi.org/10.1007/s43621-025-02168-8

[15] Leal-Filho, W., May, J., May, M. and Nagy, G. J. (2023). Climate change and malaria: Some recent trends of malaria incidence rates and average annual temperature in selected sub-Saharan African countries from 2000 to 2018. *Malaria Journal, 22*, 248. DOI: https://doi.org/10.1186/s12936-023-04682-4

[16] Monteiro, G.M., Sonounameto, R.C., Djogbenou, L.S. and Sedda, L. (2025). Spatial and spatio- temporal analysis for malaria hotspot identification: a scoping review protocol. *BMJ Open*, *6; 15(6):*

e101375. DOI: 10.1136/bmjopen-2025-101375

[17] Ogoro, M., Chijioke-nwauche, I., Yaguo-ide, L., Awopeju, A. T. O., Paul, N., Oboro, I., Kasso, T., Siminialayi, I., Abam, C., Nte, A., Nduka, F., Obunge, O., & Nwauche, C. (2022). Geospatial mapping of the burden of malaria in port. *Quest Journals Journal of Medical and Dental Science Research*, *9*(9), 109–116.

[18] Olagundoye, K., & Goparaju, L. (2023). Spatial analysis and mapping of malaria risk areas using multi- criteria decision making in Ibadan, Oyo state, Nigeria. *Journal of Geography and Cartography*, *6*(2), 1–17. DOI: https://doi.org/10.24294/jgc.v6i2.2214

[19] Rahman, M.S. and Shiddik, M.A.B. (2025). Unraveling global malaria incidence and mortality using machine learning and artificial intelligence–driven spatial analysis. *Scientific Reports, 15*, 28334. DOI: https://doi.org/10.1038/s41598-025-12872-0

[20] Singh, P. and Saran, S. (2024). Identifying and predicting climate change impact on vector-borne disease using machine learning: Case study of *Plasmodium falciparum* from Africa. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 48*(2), 387 – 390. DOI: https://doi.org/10.5194/isprs-archives-XLVIII-2-2024-387-2024

[21] Touré, M., Keita, M., Kané, F., Sanogo, D., Kanté, S., Konaté, D., Diarra, A., Sogoba, N., Coulibaly, M. B., Traoré, S. F., Alifrangis, M., Diakité, M., Shaffer, J. G., Krogstad, D.J. and Doumbia, S. (2022). Trends in malaria epidemiological factors following the implementation of current control strategies in Dangassa, Mali. *Malaria Journal, 21*(65). DOI: https://doi.org/10.1186/s12936-022-04058-0

[22] Ukawuba, I. and Shaman, J. (2022). Inference and dynamic simulation of malaria using a simple climate-driven entomological model of malaria transmission. *PLoS Computational Biology*, *18*(6), e1010161. DOI: https://doi.org/10.1371/journal.pcbi.1010161

[23] White, N.J. (2017). Identifying Malaria Hot Spots. *The Journal of Infectious Diseases*, *216, 9(1)*: 1051 – 1052. DOI: https://doi.org/10.1093/infdis/jix330

[24] World Health Organization (WHO). (2023). World Malaria Report 2020. Geneva: World Health Organization. Available at: https://www.who.int/publications/i/item/9789240079364

[25] Yakudima, I. I., Adamu, Y. M., Samat, N., Mohammed, M. U., Abdulkarim, I. A. and Hassan, N.I. (2022). Geospatial analysis of malaria prevalence among children under five years in Jigawa State, North West, Nigeria. *Research Square*. DOI: https://doi.org/10.21203/rs.3.rs-1506321/v2

[26] Yamba, E. I., Fink, A. H., Badu, K., Asare, E. O., Tompkins, A. M. and Amekudzi, L. K. (2023). Climate drivers of malaria transmission seasonality and their relative importance in Sub Saharan Africa. *GeoHealth*, *7*, e2022GH000698. DOI: https://doi.org/10.1029/2022GH000698

[27] Zhou, G., Githure, J., Lee, MC. Zhong, D., Wang, X., Atieli, H., Githeko, A., Kazura, J. and Yan, G. (2024). Malaria transmission heterogeneity in different eco- epidemiological areas of western Kenya: a region-wide observational and risk classification study for adaptive intervention planning. *Malaria Journal, 23*, 74. DOI: https://doi.org/10.1186/s12936-024-04903-4

TABLES AND FIGURES

Table 1: Model Assumptions

Zone	Mean Annual Malaria Incidence	Trend Behaviour	Seasonal Pattern	Climate Link
Sahelian (SaSZ)	160–230 cases/1000	Weakly increasing, erratic peaks (2016 & 2020)	Short rainy-season spike (July–September)	Highly variable rainfall, low humidity
Transitional (TZ)	210–320 cases/1000	Moderate fluctuations, gradual recovery	Moderate wet-season peaks (June–September)	Intermediate rainfall and vegetation
Sudan–Savanna (SuSZ)	300–420 cases/1000	Consistently high, upward trend	Pronounced peaks (May–October)	Persistent rainfall, dense vegetation

Source: Fieldwork, 2024

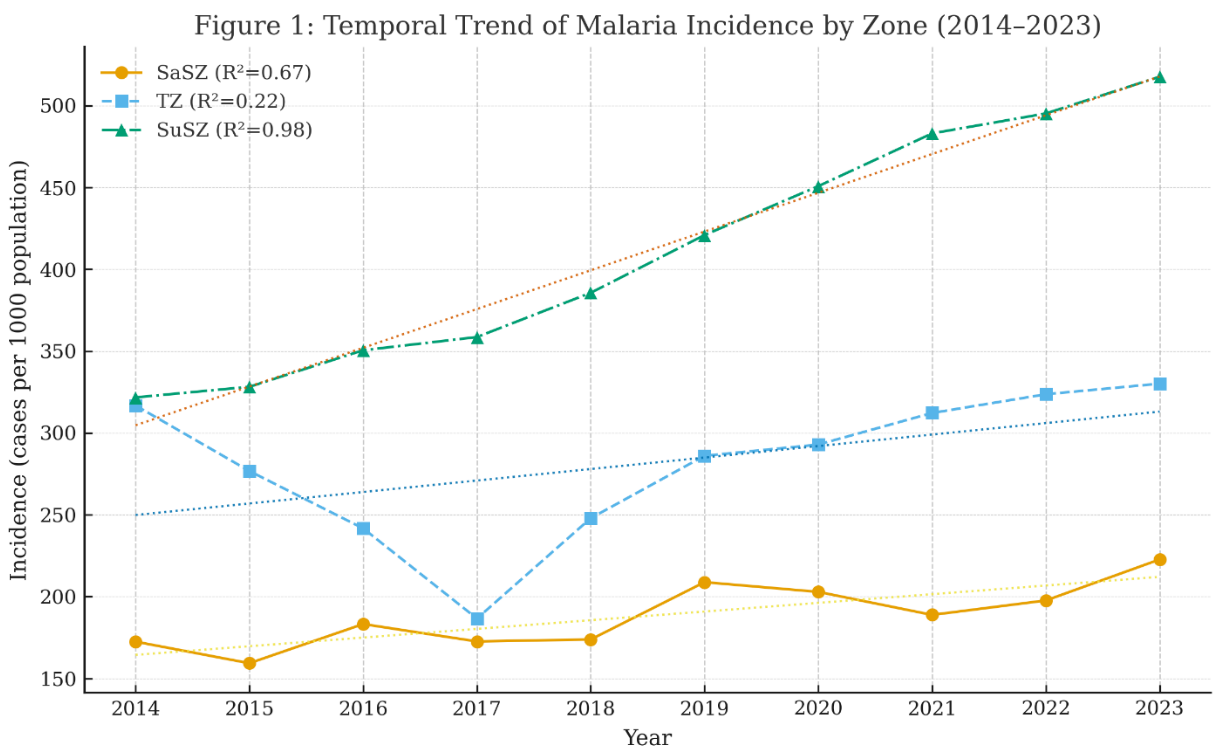

Figure 1: Temporal Trends of Malaria Incidence
Source: Fieldwork, 2024

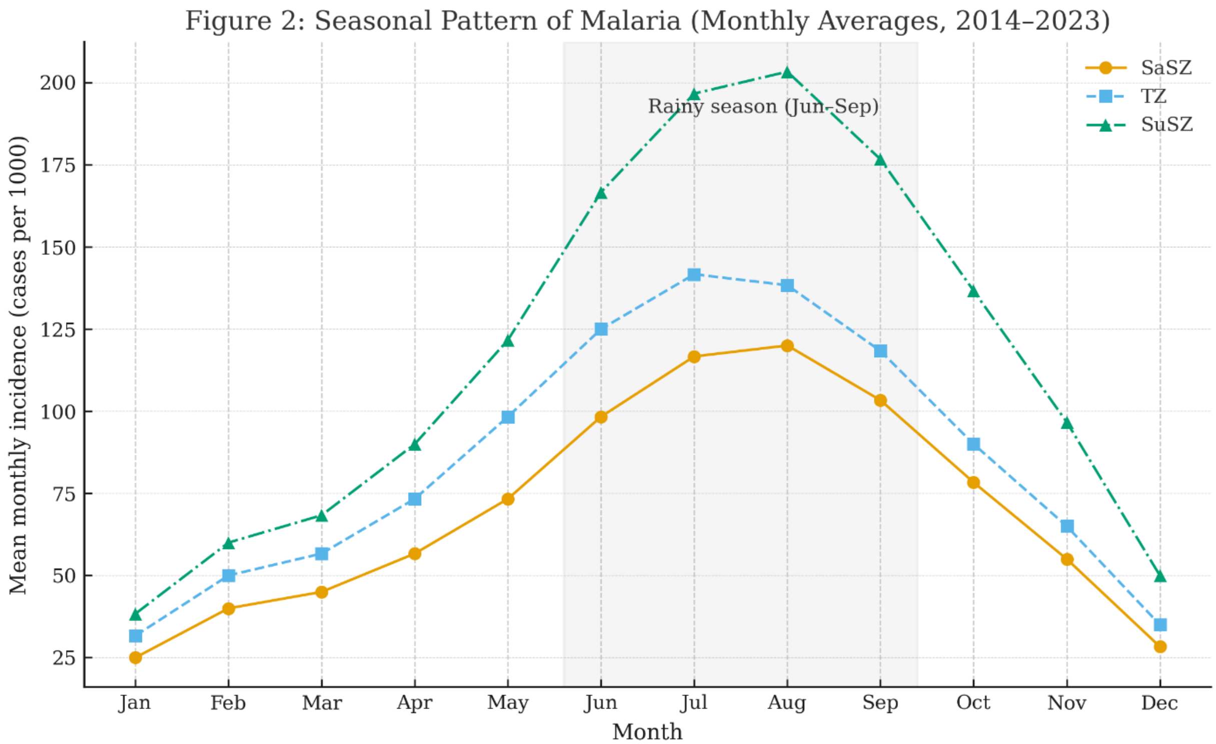

Figure 2: Seasonality of Malaria Incidence (Monthly Averages)
Source: Fieldwork, 2024

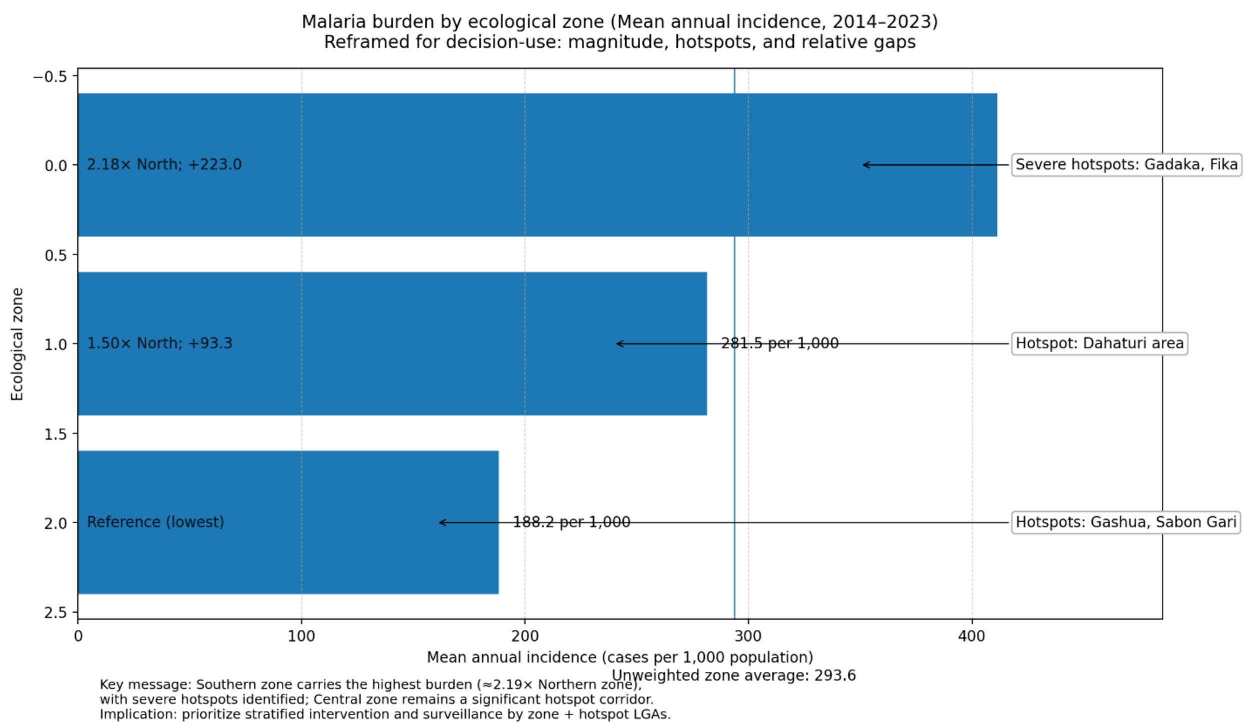

Figure 3: Spatial Distribution and Zone-Level Variation of Malaria Burden
Source: Fieldwork, 2024

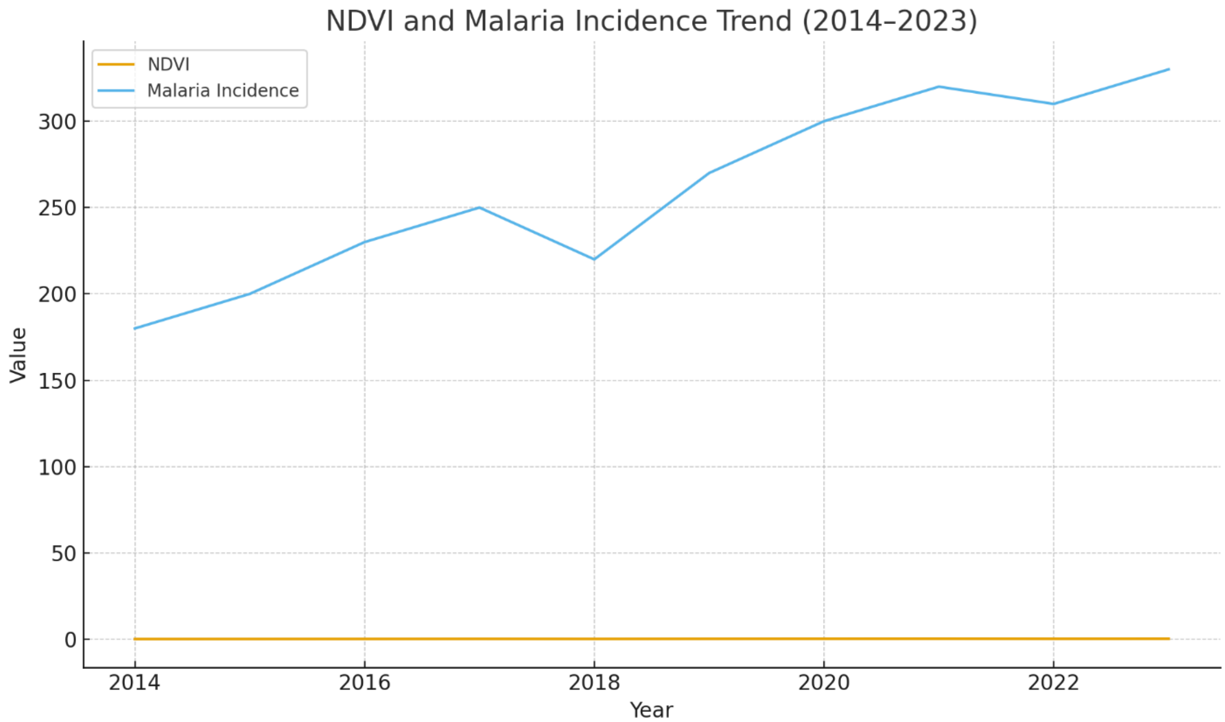

Figure 4: NDVI-Malaria Trend Incidence
Source: Fieldwork, 2024

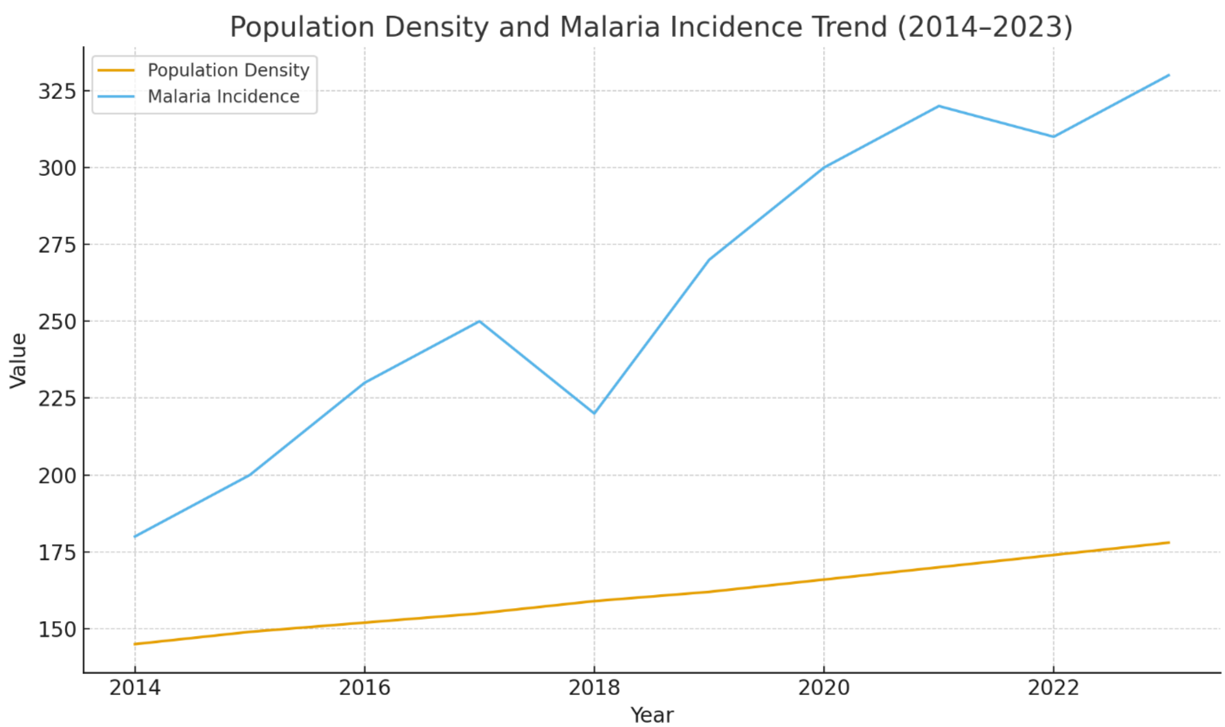

Figure 5: Population Density-Malaria Trend Incidence
Source: Fieldwork, 2024