

Spatial Distribution and Environmental-Climatic Determinants of Malaria Infection Among Children Under Five in Liberia

Richard Sagacity Tugbeh

rt5716@srmist.edu.in

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

Veliah Geetha

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

Samadou Tchakondo

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

Komi Selassi Gayi

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

George B. Davis

Quantitative-Data for Decision-Making (Q4D) Lab

Josiah Brown Wilson

William V. S. Tubman University

Ayao Sangénis Assogba

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

Yendouname Kandjoni

SRM Institute of Science and Technology, Kattankulathur Campus, Chengalpattu - 603203

Stephen W. Picka

, Harvard University, 641 Huntington Avenue Boston

Research Article

Keywords: Spatial analysis, Malaria, Children under-five, Liberia, Climate, Environment

Posted Date: July 3rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10148866/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Background: Malaria remains a serious public health threat in Sub-Sahara Africa with children under five years bearing the heaviest burden. However, Liberia is considered hyperendemic for malaria and its tropical and a predominantly equatorial climate that is warm and humid, provides ideal breeding conditions for *Anopheles* mosquitoes and year-round transmission. The study aimed to examine the spatial pattern of malaria infection and assess the influence of climatic and environmental factors on malaria risk among children under five in Liberia.

Method: A quantitative secondary analysis was conducted using data from the 2022 Liberia Malaria Indicator Survey and other sources containing the environmental and climatic variables. The study focused on children under five years in the 150 LMIS 2022 clusters of all the 15 counties in Liberia. Moran's I was used to assess the presence of spatial autocorrelation, while the existence of local clustering was examined using Local Indicators of Spatial Association (LISA). The Ordinary Least Squares (OLS) and the Spatial Lag analyses (SLM) were performed to explore the relationship between malaria infection and environmental and climatic drivers.

Result: The study revealed substantial spatial heterogeneity in under five malaria across Liberia. Some survey clusters (0%) showed very low prevalence but the highest cluster (81%) was in Sinoe county. Global Moran's I (0.111, $p = 0.002$) indicated weak but significant clustering, and LISA maps highlighted significant hotspots in Southern and Southeastern counties versus coldspots in Northwest. The regression results pinpointed rainfall ($\beta = 0.083$, $p < 0.003$), vegetation ($\beta = 0.055$, $p < 0.009$), and water proximity ($\beta = 0.701$, $p < 0.026$). The SLM (AIC = 1184.01) outperformed OLS (AIC = 1185.13) model.

Conclusion: The study demonstrated that malaria prevalence among children under five is characterized by pronounced spatial heterogeneity driven by climate and geography. High rainfall, dense vegetation, and proximity to water bodies create favorable conditions for transmission, especially in the southern counties. It also revealed clusters of high risk that extend beyond local environmental suitability, indicating spillover effects. These findings underscore the need for geographically differentiated malaria control strategies in Liberia, focusing intensified efforts on the identified hotspot counties/regions.

Background

Malaria remains one of the most important infectious diseases in sub-Saharan Africa, and young children carry the heaviest burden. The WHO reported that in 2024 there were an estimated 282 million malaria cases and 610,000 deaths globally, with the African Region accounting for about 94% of cases and 95% of deaths; children under five in Africa were responsible for nearly three-quarters of malaria deaths in the region [1].

Malaria remains a leading cause of illness among Liberian children under five, but recent data show dramatic progress: Liberia's 2022 Malaria Indicator Survey (MIS) reports only 10% prevalence in children (down from 27% in 2011) [2]. Liberia is considered hyperendemic for malaria, with *Plasmodium falciparum* causing 98% of the infections [3][2]. However, malaria risk is highly spatially heterogeneous. In-depth analysis of the 2022 LMIS found significantly higher prevalence in inland counties (12.7%) than coastal ones (8.3%) [4], and enduring hotspots in certain southeast counties (e.g., Rivercess, Sinoe, Maryland) noted by the National Malaria Control Program (NMCP) [2]. Key demographic and socioeconomic risk factors include lack of bed net use, childhood anaemia, poverty, and rural residence [4].

Liberia has tropical and a predominantly equatorial climate characterized by consistently warm, humid conditions and provides ideal breeding conditions for *Anopheles* mosquitoes and year-round transmission [5][6]. Rainfall is abundant > 3000 mm annually with a long-wet season roughly May–October and a short dry season (December–February) [3]. Coastal counties experience very high rainfall, swamps, and mangroves, whereas inland highlands are cooler with a pronounced dry season [5]. These geographic and climatic gradients lead to spatial heterogeneity in malaria ecology: coastal areas sustain perennial transmission due to humidity and wetlands, while inland areas see more seasonal peaks driven by rainfall and temperature [6][7].

In general, climatic (temperature, rainfall, aridity) and environmental (vegetation, proximity to water, elevation) factors are key determinants of malaria risk. These factors create suitable conditions for developing malaria vectors and parasites [8–13]. Incorporating climate data helps predict where and when outbreaks may occur.

The broader epidemiologic literature also shows that spatial methods are well suited for studying place-based disease patterns. A review of spatial methods in epidemiology found that clustering, spatial smoothing, interpolation, and spatial regression are among the most commonly used approaches in public health, especially where proximity and local spatial dependence matter [14].

Taken together, these findings suggest that malaria in Liberia is likely influenced not only by individual and household characteristics, but also by climatic and environmental conditions that vary across space. Rainfall may create breeding habitats, temperature affects parasite development and mosquito survival, vegetation can indicate habitat suitability, elevation may proxy cooler and less suitable environments, and proximity to water bodies can increase exposure to mosquito breeding sites. However, previous studies have mostly relied on county-level, region-level or aggregated spatial summaries, which can miss fine-scale geographic variation within and between survey clusters [4,14–20].

Despite the growing body of malaria research in sub-Saharan Africa, most existing studies have relied on point coordinates and administrative-level (e.g., region, county or district) aggregations or coarse spatial summaries [4, 14–20]. Such approaches may obscure important fine-scale geographic heterogeneity and fail to capture localized variations in malaria transmission within and between survey clusters. In Liberia, spatial epidemiological

work is still limited, and previous studies have mainly examined overall prevalence and demographic or socioeconomic factors rather than spatial clustering or environmental influences [3, 4, 15, 16]. This leaves an important gap in understanding how malaria is distributed across space in the country.

So far, no study has fully applied spatial regression and spatial autocorrelation methods, such as Global Moran's I and Local Moran's I, to identify malaria hotspots and coldspots among children under five in Liberia. Filling this gap is important for understanding spatial patterns and supporting targeted malaria control.

This study addresses that gap by using the LMIS 2022 cluster polygon shapefile to carry out a fine-resolution spatial analysis of malaria infection. Using cluster polygons allows more accurate linkage between survey data and raster-based climatic and environmental variables, improving measurement of environmental exposure at cluster level. This provides a more detailed assessment of how climatic and ecological factors influence malaria risk and whether observed clustering is due to environmental conditions rather than random geographic variation. In this way, the study examines the spatial pattern of malaria infection among children under five and assesses the influence of climatic and environmental factors on malaria risk among children under five in Liberia.

Methods

Setting and Target Population

Liberia is Africa's oldest independent republic. The country is located on the west coast of Africa. It is bordered by the Atlantic Ocean to the southwest, Sierra Leone to the west, Guinea to the south, and Ivory Coast to the east. Liberia's climate is tropical, hot, and humid all year round, and has an area of 111,369 square kilometers. The country is divided into 15 political subdivisions called Counties (Fig. 1), with a population of 5.3 million people [21, 22]. The study focused on children under five years in the 150 LMIS 2022 clusters (both rural and urban) of all the 15 counties in Liberia.

Study Design

This study adopted a quantitative approach by performing a secondary analysis of the 2022 Liberia Malaria Indicator Survey (LMIS). This nationally representative, cross-sectional dataset is refreshed every five years, with the most recent data collection occurring between October 4 and December 12, 2022.

The 2022 LMIS was a collaborative effort led by the Ministry of Health's National Malaria Control Program and the Liberia Institute of Statistics and Geo-Information Services (LISGIS). The primary objective of the 2022 LMIS was to offer updated data to assist policymakers, planners, researchers, and program managers. The survey also provided population-based prevalence estimates for anemia and malaria among children aged 6–59 months. A Standardized household cluster sampling methods were applied [2, 4]

Sampling Techniques and Sample Size

The 2022 LMIS utilized a two-stage sample design grounded in the sampling frame of the 2008 National Population and Housing Census (NPHC). In the first stage, 150 clusters were randomly selected using probability proportional to size. This included a distribution of 70 urban and 80 rural clusters. In the second stage, researchers systematically selected 30 households per cluster, targeting a total of 4,500 households. Of these, 4,306 households were successfully enumerated [2,4]

From the initial 150 clusters, this study focused on a weighted sample size of 2,864 children aged 6–59 months who underwent testing [2, 4].

Data Source

This study used data accessed from the official database of the Demographic and Health Surveys (DHS) Program (<https://dhsprogram.com/>), Global Climate data 2020 <https://www.worldclim.org> (temperature, aridity), Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) 2022 <https://www.chc.ucsb.edu/data/chirps> (rainfall), HydroRIVERS 2025 <https://www.hydrosheds.org/hydroatlas> (proximity to water), and U.S. Geological Survey 2022 <https://earlywarning.usgs.gov/> (Enhance Vegetation Index) [23 – 2].

The 2022 LMIS data which is the major dataset, employed three questionnaires: the biomarker questionnaire, the women's questionnaire, and the household questionnaire. Country specific topics included questions concerning the 2021 mass insecticide-treated net (ITN) distribution campaign, the acceptability of the new malaria vaccine, and mass drug administration of seasonal malaria chemoprevention for children were among the topics covered in the questionnaires, which were based on the DHS programs model questionnaires and modified to reflect the population and health issues pertinent to Liberia [2, 4].

All women age 15 to 49 who were either regular inhabitants of the selected households or guests who remained in the family the night before the survey were eligible to be interviewed with the parents or guardians' consent. All children age 6–59 months were tested for anemia and for malaria infection [2, 4].

Study variables and Measurement

The selection of both the outcome and explanatory variables used for this study were strictly guided by an extensive literature review and a conceptual framework [7–11, 13, 14, 17–20, 23]. This ensured that the analysis accounted for known determinants of health outcomes while maintaining theoretical consistency.

Outcome variable

The dependent variable of this study was malaria prevalence and was measured using variable HML32 from the 2022 Liberia Malaria Indicator Survey. Malaria status was determined by microscopy testing and defined according to the WHO Statistics guidelines as the proportion of children classified as malaria – positive at the time of the survey [2, 23]. Malaria status was treated as a binary variable and coded as 1 = positive and 0 = negative.

Explanatory variables

The independent variables were grouped as environmental and climatic variables. To account for the ecological determinants of malaria transmission, these environmental and climatic variables were integrated into the analysis [17–20]. These variables were selected based on their established role in defining the habitable niche for Anopheles vectors and the developmental rate of the Plasmodium parasite:

- **Temperature:** Represented as the mean monthly temperature (°C). Ambient temperature is a critical driver of the extrinsic incubation period of the parasite.
- **Aridity:** An aridity index scaled from driest to wettest conditions. This serves as a proxy for environmental moisture, which is essential for adult mosquito longevity.
- **Rainfall:** Measured as the average monthly rainfall (mm). Precipitation levels directly influence the availability and stability of larval breeding sites.
- **Proximity to Water:** Calculated as the linear distance to the nearest permanent water bodies (km), representing the proximity of households to consistent vector breeding grounds.
- **Enhanced Vegetation Index (EVI):** The mean vegetation index value, used to assess chlorophyll abundance. This variable acts as a robust indicator of environmental humidity and suitable resting habitats for mosquitoes.

These continuous variables were extracted and matched to the LMIS cluster locations.

Data Processing and Statistical Analysis

Data processing

To ensure data quality, data analysis was conducted using these software: R statistical software (version 4.4.1; R Foundation for Statistical Computing, Vienna, Austria) was employed for data cleaning, transformation and analysis, QGIS (version 3.44.1, -Solothurn) was used for geographic information system tasks, especially for extracting values from raster files and designing the final study maps, and GeoDa (version 1.22.0.20, Luc Anselin) was used to conduct spatial statistics. This workflow was adopted to ensure data quality and reproducibility of result.

The analysis primarily utilized the household member dataset from the 2022 Liberia Malaria Indicator Survey, especially targeting malaria – related health indicators for children aged 6–59 months.

To create the final spatial dataset, the environmental and climatic variables were integrated from these sources: the Global Climate data 2020 (temperature, aridity), Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) 2022 (rainfall), HydroRIVERS 2025 (proximity to water), and US Geological Survey 2022 (enhance vegetation index). The values of these variables (temperature, aridity, rainfall, proximity to water, enhance vegetation index) were extracted from individual raster files and matched to the LMIS cluster locations. Using a common identifier (county name and cluster ID), the environmental and climatic variables were with the malaria prevalence from the LMIS dataset and 2022 LMIS shapefile.

Data Analysis Procedures

The statistical analysis incorporated both non-spatial and spatial modelling techniques to evaluate relationship between malaria prevalence and environmental and climatic drivers. The aim of using both spatial and non-spatial models was to identify the best-fitting models for predicting malaria infection in children, and also produce the malaria risk map. To determine the superior model, we utilized the Akaike Information Criterion (AIC) [17,28,29].

First, malaria prevalence among children Under 5 (aged 6–59 months) was estimated at clusters level as a parameter using other factors in accordance with the guide to DHS Statistics (DHS-8) [30]. To calculate malaria prevalence, the household member dataset was used. The numerator consisted of the number of de facto children tested using microscopy who are positive for malaria and was represented by these variables (Household selected for hemoglobin (hv042) = 1, Slept last night (hv103) = 1, Child's age in months (hc1) in 6:59, and result of malaria rapid test (hml32) = 1). The denominator consisted of all de facto children tested for malaria using microscopy, regardless of the test result and was represented by these variables

(Household selected for hemoglobin (hv042) = 1, Slept last night (hv103) = 1, Child's age in months (hc1) in 6:59, and result of malaria rapid test (hml32) in 0,1). The malaria prevalence was calculated as numerator divided by the denominator, multiplied by 100 [4, 30].

Moreover, the values of the environmental and climatic factors (temperature, aridity, rainfall, proximity to water, enhance vegetation index) were extracted from individual raster files at the cluster level.

Moran's I statistics was used to assessed both the presence of spatial autocorrelation or clustering on malaria prevalence and the overall spatial autocorrelation between an ecological predictor and malaria prevalence [31–32]. A Moran's I scatter plot was used to provide a comprehensive overview of the global spatial autocorrelation of malaria prevalence. This determine whether malaria prevalence across Liberia exhibited an overall tendency toward spatial clustering, dispersion, or randomness [17, 32–33]. To move beyond global trends and identify specific geographic clusters, a Local Indicators of Spatial Association (LISA) analysis was conducted to detect significant local hot spots (areas of high incidence surrounded by high incidence) and cold spots (areas of low incidence surrounded by low incidence) of cluster locations [17, 32–33].

To explore the relationship between malaria infection and environmental and climatic drivers (temperature, aridity, rainfall, proximity to water, enhance vegetation index), Ordinary Least Squares (OLS) and the Spatial Lag analyses (SLM) were performed. The OLS regression was used as the baseline global model to quantify the relationship between the independent covariates and the dependent variable [28]. This non-spatial approach provides covariate-adjusted estimates and predicts the mean risk of malaria across the study area [29].

To address potential spatial dependency, the SLM was implemented. This model incorporates a spatially-lagged dependent variable, which accounts for the influence of malaria prevalence in neighboring clusters on the index cluster. By utilizing a spatial weight matrix, the SLM effectively adjusts for spatial autocorrelation inherent in the distribution of the disease, reflecting the neighborhood effect of transmission [31–33].

Based on the Anselin Decision Rule, the Spatial Lag Model (SLM) was adopted for the final spatial analysis. This decision was supported by significant results in both the standard Lagrange Multiplier (LM-lag) and robust LM-lag diagnostics ($p < 0.05$), whereas the LM-error statistics remained non-significant, indicating that the spatial dependency in the data is best captured through a spatially-lagged dependent variable [34]. Multicollinearity among explanatory variables was assessed using variance inflation factors (VIF) [35].

Results

Spatial distribution of Malaria prevalence in Liberia

Figure 2. below, shows the spatial distribution of under-five malaria prevalence across the country. This spatial distribution map indicates marked geographic variation in malaria prevalence among children under five across Liberia, with clusters of low, moderate, and high prevalence observed in different parts of the country. The cluster with the highest malaria prevalence (81%) is found in Sinoe county. This indicates that malaria risk varies from place to place rather than being uniformly spread across Liberia.

Spatial Autocorrelation: Global Moran's I

The global Moran's I test for malaria prevalence (Moran I = 0.111, $p = 0.002$) showed weak positive spatial autocorrelation, suggesting that malaria infection among under five was not randomly distributed across Liberia (Fig. 3). After adjusting for the selected climatic and environmental covariates, the residual Moran's I declined to ($I = 0.067$, $p = 0.032$), indicating that the model explained part of the observed spatial pattern. However, the persistence of a small residual spatial autocorrelation suggests that some spatial dependence remains unexplained, possibly due to unmeasured environmental factors.

Spatial Autocorrelation: Local Indicators of Spatial Association (LISA)

As shown in Fig. 4(a & b), Local Indicators of Spatial Association (LISA) was used to examine the presence of local spatial clustering of malaria prevalence among children under five in Liberia. The LISA cluster map revealed distant spatial pattern, including statistically significant hotspots and coldspots. High-High (HH) clusters (Dark-red), representing areas with high malaria prevalence surrounded by similar high-prevalence neighbors, were predominately observed Southern and South-East regions of the country. In contrast, Low-Low (LL) clusters (Dark-blue), indicating areas of low malaria prevalence surrounded by similar low-prevalence neighbors, were mainly observed Western and North- West and Central regions.

Additionally, a small number of outliers were identified, including Low-High (LH) clusters (Light-blue), low-prevalence areas surrounded by high-prevalence neighbors, and High-Low (HL) clusters (Light-red), high-prevalence areas surrounded by low-prevalence neighbors. This finding suggests localized inconsistencies or transition zones in malaria transmission patterns.

The LISA significant map further confirmed that a subset of clusters exhibited statistically significant spatial auto correlation at varying levels ($p \leq 0.05$, $p \leq 0.01$, and $p \leq 0.001$). These significant clusters were primarily concentrated in the southern corridor and selected western regions, reinforcing the presence of localized malaria hotspots and coldspots. Overall, the findings demonstrate that malaria prevalence in Liberia exhibits localized spatial clustering, highlighting the importance of geographically targeted interventions.

Environmental and Climatic Drivers of Malaria from OLS &SLM, and Model fit

The ordinary least squares (OLS) model presented in Table 1&2, showed that climatic and environmental variables explained moderate proportion of the variation in malaria prevalence among under-five children in Liberia ($R^2 = 0.261$; adjusted $R^2 = 0.182$). In this model, the mean annual rainfall ($\beta = 0.083$, $p < 0.003$) and enhanced vegetation index ($\beta = 0.055$, $p < 0.009$) were significant positive predictors of malaria prevalence, indicating that malaria burden tended to increase in areas with higher rainfall and greener vegetation. Proximity to water ($\beta = 0.701$, $p < 0.026$) was also associated with malaria prevalence. This is a very strong driver in this model, suggesting that being closer to Liberia's numerous water bodies (rivers, lagoons, wetlands) significantly increases the local risks. However, the OLS diagnostics indicated the presence of spatial dependence, with Moran's I for the residuals being significant. The significant robust LM lag test, together with the significant LM lag test, suggested that a spatial lag specification was more appropriate than a spatial error model.

As also shown in Table 1, the spatial-lag model provided a slightly better fit to the data than the OLS model, with a higher R^2 (0.305 vs. 0.181), a lower AIC (1184.01 vs. 1185.13). The spatial dependence parameter ($\rho = 0.290$, $P < 0.045$) was positive, suggesting that malaria prevalence in one cluster was significantly influenced by prevalence in neighboring clusters. Similarly, In the spatial-lag model, rainfall, NDVI, and the proximity to water variables remained statistically significant. Taken together, these findings indicate that malaria risk in Liberia is not shaped only by local environmental and climatic conditions, but also by significant spatial spillover effect from neighboring clusters.

Table 1
Non-spatial and Spatial models showing correlation between the mean malaria prevalence and climatic and environmental variables.

Predictors	Ordinary Least Squares (OLS)		Spatial Lag Model (SLM)	
	Coefficient (B) (%)	P-value	Coefficient (B) (%)	P-value
Mean Annual Rainfall	0.083	0.003	0.068	0.018*
Mean Temperature	-1.041	0.565	-0.500	0.773
Aridity	0.035	0.566	0.031	0.587
Enhanced Vegetation Index	0.055	0.009	0.047	0.015*
Proximity to water	0.701	0.026	0.595	0.016*
Lag (Rho)	-	-	0.289	0.045*
R^2	0.261	-	0.305	-
Adjusted R^2	0.182	-	-	-
AIC	1185.13	-	1184.01	-
. Note : * denotes significance p-value				

Table 2
Diagnostics for spatial dependence for weight matrix

Test	Moran's I/DF	Value	P-value
Moran's I (error)	0.067	2.229	0.025*
Lagrange Multiplier (lag)	1	4.319	0.037*
Robust LM (lag)	1	5.730	0.016*
Lagrange Multiplier (error)	1	2.099	0.147
Robust LM (error)	1	3.509	0.061
Lagrange Multiplier (SARMA)	2	7.829	0.019*
Note : * denotes significance p-value			

Discussion

Malaria remains hyperendemic in Liberia and continues to be a leading cause of morbidity among children under five, although recent data indicates substantial progress [2, 3]. This research integrated both non-spatial and spatial regression analyses to map malaria hotspots and determine the climatic and environmental factors influencing malaria transmission across Liberia.

The study revealed substantial spatial heterogeneity in under-five malaria prevalence across Liberia. Some survey clusters exhibited very low prevalence (0%) while others are extremely high; the highest cluster (81%) was in Sinoe County. This confirms that malaria risk is not uniform

nationwide but concentrated in specific hotspots. In particular, the coastal Southeastern counties (e.g., Sinoe, Maryland, Grand Kru) and some northern inland areas (e.g., Lofa, Bong) emerged as high-burden regions [4]. This pattern agrees with other surveys and reinforces our findings that Liberia's malaria burden is intensely spatially clustered, with certain counties experiencing far higher transmission. These spatial patterns likely reflect underlying ecological gradients (e.g. rainfall, vegetation) and social conditions (e.g. poverty, housing) that vary regionally [2–4, 6].

The Global Moran's, although weak but statistically confirmed the consistent clustering of malaria prevalence which is consistent with the map's visible hotspots and coldspots. This indicates that malaria cases are naturally clustered, aligning with these studies conducted in Togo, Tanzania, Kenya and Rwanda [17, 31, 35, 36] which highlighted the importance of geographically targeted interventions to disrupt transmission clusters.

Spatial analysis through LISA underscored the localized nature of malaria transmission in Liberia, pinpointed critical High-High (HH) hotspots in the southern and south-eastern regions. These findings suggest that in areas of high ecological favorability, the absence of robust intervention coverage may worsen the disease burden. In contrast, the Low-Low (LL) coldspots observed in the western and north-central regions point toward the protective benefits of urban infrastructure and concentrated malaria control programs. Furthermore, the presence of spatial outliers indicates that local environmental anomalies can create significant deviations from regional patterns, necessitating highly granular, site-specific public health strategies [4, 17].

The regression analysis revealed rainfall, vegetation, proximity to water as key environmental and climatic drivers of malaria risk in Liberia. The emergence of rainfall as a strong positive predictor aligns with the known entomological drivers of malaria in tropical West Africa. In Liberia, heavy precipitation precipitates the formation of stagnant water bodies and poorly drained pools, creating a proliferation of breeding sites that sustain high vector densities and year-round transmission [17, 31, 38, 39]. Rainfall does not only increase larval habitats but also influences vector population dynamics and the extrinsic incubation period of Plasmodium parasites, thereby amplifying transmission intensity. The findings showed Enhanced Vegetation Index (EVI) as a significant environmental predictor of malaria prevalence which aligns with established research in diverse tropical ecosystems [17, 31, 40, 41]. The positive association between EVI values and malaria risk observed in this study is supported by evidence from Togo, Tanzania and Gabon [17, 31, 42]. This relationship is largely driven by the influence of vegetation density on vector ecology; specifically, dense canopy cover provides the shaded, humid microclimates essential for both larval development and the increased survival of adult mosquitoes, thereby intensifying the transmission cycle [42]. The finding revealed Proximity to water bodies as a significant positive predictor of malaria, indicating that living near Liberia's rivers, swamps or lagoons sharply increases local malaria risk which aligns with other regional studies [29, 43]. Literature suggests that the proximity of residence to permanent water bodies is a primary determinant of prevalence, as these surfaces provide stable environments for mosquito oviposition. While Anopheles mosquitoes can breed in any stagnant water persisting for at least 10–15 days, permanent reservoirs offer a more dangerous advantage: they bypass seasonal constraints. Consequently, children living in close proximity to these reservoirs are exposed to continuous vector recruitment, leading to higher infection rates compared to those in more distant inland clusters [29, 43].

In contrast with the study's findings, temperature and aridity were not significant predictors of malaria risk in both the non-spatial and spatial models, possibly because Liberia's climate is uniformly hot and humid which keeps malaria transmission seasonally high during both rainy seasons.

The spatial-lag model outperformed OLS and passed Lagrange tests for spatial dependence, so it is preferred. The positive spatial lag means that malaria prevalence in one cluster is significantly influenced by prevalence in adjacent clusters. This suggests malaria transmission spills over between adjacent communities, a finding also seen in regional studies [17, 43]. This spatial dependence may arise from human or mosquito movement between communities or shared environmental features.

From a public health policy perspective, these findings strongly advocate for a transition toward geographically targeted interventions. These findings support the development of spatially explicit early warning systems integrating climatic predictors to guide timely malaria interventions. While Liberia has achieved a commendable 44% reduction in malaria incidence through mass insecticide-treated net (ITN) distribution [44], further progress toward elimination necessitates a departure from uniform national strategies. Given the extreme spatial heterogeneity identified in this study, resources should be prioritized for hyper-endemic hotspots such as Sinoe, Maryland and Grand Kru counties. Hotspot counties (Sinoe, Grand Kru, etc.) may benefit from intensified vector control (e.g. indoor residual spraying, larval source management) and additional bed net and vaccine campaigns timed before the rainy season peak. Community education on consistent ITN use and prompt treatment seeking is also critical in high-risk zones. Nationwide strategies should be adjusted to focus resources where risk is clustered, rather than uniform deployment.

Finally, While the spatial lag model provided improved model fit and accounted for spatial dependence, more advanced spatial modelling approaches could further enhance inference. Future work could incorporate Bayesian spatial models (e.g., conditional autoregressive (CAR) or Besag–York–Mollié (BYM) models) to better capture unobserved spatial heterogeneity and quantify uncertainty in malaria risk estimates.

Limitations

This study uses recent national survey data and high-resolution spatial analysis, providing one of the first fine-scale malaria risk maps for Liberia. However, it has constraints. Environmental covariates from satellite, have inherent measurement error and may not capture micro-scale variations. Other factors like health care access, housing and occupation were not directly modelled which could confound the results.

Finally, the findings reflect malaria infection patterns among children aged 6–59 months in Liberia during the LMIS data collection period (October–December 2022). Seasonal variation in malaria transmissions may limit the extent to which these results represent year-round patterns.

Conclusion

This study confirmed the complex interplay between environmental and climatic determinants and the spatial distribution of pediatric malaria in Liberia. The findings demonstrate that malaria prevalence among children under five is characterized by pronounced spatial heterogeneity driven by climate and geography. High rainfall, dense vegetation, and proximity to water bodies create favorable conditions for transmission, especially in the southern counties. Spatial analysis reveals persistent clusters of high risk that extend beyond local environmental suitability, indicating spillover effects. These findings underscore the need for geographically differentiated malaria control strategies in Liberia, focusing intensified efforts on the identified hotspot counties/regions. By prioritizing resources in identified high-burden clusters, the National Malaria Control Program can optimize impact, sustain recent gains, and accelerate progress toward the 2030 elimination goals.

Abbreviations

AIC	Akaike Information Criterion
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
DHS	Demographic Health Survey
HH	High–High
HL	High–Low
ITN	Insecticide–Treated Net
LL	Low–Low
LH	Low–High
LISA	Local Indicators of Spatial Association
LISGIS	Liberia Institute of Statistics & Geo–Information Services
LMIS	Liberia Malaria Indicator Survey
NMCP	National Malaria Control Program
NPHC	National Population & Housing Census
OLS	Ordinary Least Squares
SLM	Spatial Lag Model
WHO	World Health Organization

Declarations

Ethics approval and consent to participate

This study examined environmental and climatic drivers of malaria in under five children in Liberia. The primary data used in this study are publicly available data from the DHS portal and the authorization to use the dataset was granted by the DHS. Consistent with the standards in ensuring the protection of respondents’ privacy, the collected data used in the present study was anonymous and acquired participants informed consent [45]. So, there was no additional ethical permission required.

Consent to publication

Not applicable.

Competing interests

The authors affirm that the study was conducted without any financial assistance or commercialization that could impede the study as a potential conflict of interest.

Funding

No funding received for this study.

Author Contribution

Richard Tugbeh conceptualized and designed the study, conducted the data analysis and up to the preparation of the initial manuscript draft. Veliah Geetha provided supervision for the study, offered methodological guidance, and critically reviewed the manuscript for significance. Samadou Tchakondo and Komi Selassi Gayi contributed to the analytical approach and provided technical and statistical guidance during data analysis. George B. Davis provided technical support during the data analysis and as well as manuscript editing. Josiah Brown Wilson, Ayao Sangénis Assogba, Yendouname Kandjoni, and Stephen W. Picka participated in literature review, data interpretation and as well as manuscript editing. All authors reviewed and approved the final version of the manuscript.

Acknowledgement

The authors wholeheartedly extend their sincere appreciation to Dr. Muthuperumal Prakash and Dr. Harr Singh of the SRM School of Public Health for their immeasurable guidance and support throughout this work. Our appreciation also goes to the DHS Program for providing access to the Liberia Malaria Indicator Survey (LMIS) 2022 data which made this study possible. We gratefully acknowledge the financial support by SRM School of Public Health, Faculty of Medicine and Health Sciences, SRMIST, Kattankulathur for bearing the defrayed costs of publishing this article.

Data Availability

The datasets that support the conclusions of this study are accessible through the Measure DHS (<https://dhsprogram.com/>) repository, Global Climate data 2020 <https://www.worldclim.org>, Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) 2022 <https://www.chc.ucsb.edu/data/chirps>, HydroRIVERS 2025 <https://www.hydrosheds.org/hydroatlas>, and U.S. Geological Survey 2022 <https://earlywarning.usgs.gov/>. The 2022 Liberia Malaria Indicator Survey (LMIS) dataset in particular, can be obtained following request and approval from the DHS Program.

References

1. World Health Organization. (2025, December 4). *Malaria*. WHO Fact Sheets. Retrieved from <https://www.who.int/news-room/fact-sheets/detail/malaria> Accessed January 14, 2026
2. National Malaria Control Programme (NMCP), Liberia. Liberia Malaria Indicator Survey (LMIS) 2022: Final report [Internet]. Monrovia (Liberia): NMCP; 2023. Available from: <https://www.dhsprogram.com/pubs/pdf/MIS44/MIS44.pdf>. Accessed January 7, 2025.
3. Koko, V. S., Hinneh, D. L., Kumeh, O., Washington, T., Alade, J. O., Duokie, D. S.-D., Wesseh, C. S., Bawo, L., Davis, T., Zawolo, J., Konwloh, P., Jackson, D., Kollah, T. C., Jones, L., Janafo, A. S., Jeuronlon, M. K., Galatas, B., & Temu, E. A. (2025). Epidemiological stratification and sub-national tailoring of malaria interventions in Liberia. *Malaria Journal*, 24, 398. <https://doi.org/10.1186/s12936-025-05536-x>
4. Tugbeh RS, Veliah G, Jennifer HG, et al. Geographic variation in malaria prevalence among children under five in coastal and inland counties of Liberia: analysis of the 2022 Malaria Indicator Survey. *Malaria Journal*. 2026; 25:92 <https://doi.org/10.1186/s12936-026-05784-5>
5. World Bank Group. Climate Risk Country Profile: Liberia. Washington (DC): World Bank; 2021. Available from: https://climateknowledgeportal.worldbank.org/sites/default/files/2021-07/1596-WB_Liberia%20Country%20Profile-WEB.pdf. Accessed April 19, 2025
6. Koffi AA, Camara S, Ahoua Alou LP, Oumbouke WA, Wolie RZ, Tia IZ, et al. Anopheles vector distribution and malaria transmission dynamics in Gbêké region, central Côte d'Ivoire. *Malar J*. 2023; 22:192. <https://doi.org/10.1186/s12936-023-04623-1>
7. Nyasa R, Awatboh F, Kwenti TE, Titanji VPK, Ndip, Ayamba LM. The effect of climatic factors on the number of malaria cases in an inland and a coastal setting from 2011 to 206 in the equatorial rain forest of Cameroon. *BMC Infect Dis*. 2022; 22:461. <https://doi.org/10.1186/s12879-022-07445-9>
8. Traoré N, Millogo O, Sié A, Vounatsou P. Impact of climate variability and interventions on malaria incidence and forecasting in Burkina Faso. *Int J Environ Res Public Health*. 2024; 21:1487.
9. Bationo CS, Lokossou V, Landier J, Sylla B, Tougri G, Ouedraogo B, et al. Geo-epidemiology of malaria in Burkina Faso, 2013–2018: a recent re-increase. *Medrxiv*. 2021. Available from: <https://www.medrxiv.org/content/10.1101/2021.10.27.21265260v1.full>

10. Thomson MC, Ukawuba I, Hershey CL, Bennett A, Ceccato P, Lyon B, et al. Using rainfall and temperature data in the evaluation of national malaria control programs in Africa. *Am J Trop Med Hyg.* 2017;97(Suppl. S3):32–45.
11. Abiodun GJ, Maharaj R, Witbooi P, Okosun KO. Modelling the influence of temperature and rainfall on the population dynamics of *Anopheles arabiensis*. *Malar J.* 2016;15:364.
12. Okiring A, Epstein A, Namuganga JF, Kamya V, Sserwanga A, Kapisi J, et al. Relationships between test positivity rate, total laboratory confirmed cases of malaria, and malaria incidence in high burden settings of Uganda: An ecological analysis. *Malar J.* 2021; 20:42.
13. McMahon A, Mihretie A, Ahmed AA, et al. Remote sensing of environmental risk factors for malaria in different geographic contexts. 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8201719/?utm_source=chatgpt.com
14. Auchincloss AH, Gebreab SY, Mair C, Diez Roux AV. A Review of Spatial Methods in Epidemiology, 2000–2010. 2012. https://pmc.ncbi.nlm.nih.gov/articles/PMC3638991/?utm_source=chatgpt.com
15. Koko J, Kollie KK, Ballah K. Episodes of confirmed malaria and associated factors among patients attending selected health facilities, Liberia, 2015–2016. *J Intervent Epidemiol Public Health.* 2021; 4:10.
16. Bawo L, Platt EJ, Korlubah SD. Assessment of long-lasting insecticide-treated net (LLIN) ownership and utilization in households with children under five years in Grand Bassa County, Liberia. *Public Health Action.* 2012; 2:93–97. <https://doi.org/10.5588/PHA.12.0040>
17. Kombate G, Kone I, Douti B, Soubeiga KAM, Grobbee DE, van der Sande MAB. Malaria risk mapping among children under five in Togo. *Sci Rep.* 2024;14(1) :8213. <https://doi.org/10.1038/s41598-024-58287-1>
18. Animut Y, Nigatu SG, Teklu RE, Abiy SA, et al. Spatial distribution of malaria among under-five children and associated factors in Tanzania: a spatial and multilevel analysis. *Malar J.* 2025; 24:86. <https://doi.org/10.1186/s12936-025-05313-w>
19. Ugwu CLJ, Zewotir T. Spatial distribution and sociodemographic risk factors of malaria in Nigerian children less than 5 years old. *Geospat Health.* 2020;15(2). <https://doi.org/10.4081/gh.2020.819>
20. Nzabakiraho JD, Gayawan E. Geostatistical modeling of malaria prevalence among under-five children in Rwanda. *BMC Public Health.* 2021; 21:369. <https://doi.org/10.1186/s12889-021-10305-x>
21. Liberia Institute of Statistics & Geo-Information Services (LISGIS). 2022 Liberia National Population and Housing Census (NPHC): Thematic report on population size, distribution and structure. Monrovia: LISGIS; 2023. <https://lisgis.gov.lr/censusreport>. Accessed February 20, 2025.
22. Sharpe, G. Y. (2025). Integrated Summary Report of Liberia 15 County Climate Change Baseline Reports. Government of Liberia. https://ekmsliberia.info/wp-content/uploads/2025/05/Consolidated-Summary_Liberia_Climate_Change_Baseline_Reports-Final.pdf#:~:text=Liberia%E2%80%99s%20climate%20is%20tropical%2C%20hot%2C,Soil%20Types%2C%20Hydrography%2C%20and%20Vegetation Accessed February 19, 2026
23. DHS Program/ICF. Protecting the privacy of DHS survey respondents. Rockville (MD): ICF; 2019. Available from: <https://dhsprogram.com/methodology/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm> Accessed July 10, 2025
24. Fick SE, Hijmans RJ. WorldClim 2.1km climate surfaces (1970–2000) for 19 bioclimatic variables, 2020. Available from: <https://www.worldclim.org> Access December 06, 2026
25. Climate Hazards Center (UCSB). *CHIRPS v2.0* precipitations dataset (1981–2022) [Internet]. Santa Barbara: University of California; 2022. Available from: <https://www.chc.ucsb.edu/data/chirps> Access December 06, 2025
26. Lehner B, Grill G. HydroRIVERS: global river network topology from HydroSHEDS. 2025. Available from: <https://www.hydrosheds.org> Access January 06, 2026
27. United States Geological Survey. Shuttle Radar Topography Mission (SRTM) Version 3.0. Sioux Falls, SD: USGS/NASA; 2000. Available from: <https://earlywarning.usgs.gov/> Access December 06, 2025
28. Arifin SMN, Davis GJ, Zhou Y. Modeling space in an agent-based model of malaria: comparison between non-spatial and spatial models. In *Proc. of the 2011 Workshop on Agent-Directed Simulation*. 92 – 9 (San Diego, CA, USA: Society for Computer Simulation Intern
29. Onyiri, N. Estimating malaria burden in Nigeria: A geostatistical modelling approach. *Geospat. Health* 10(2), 306 (2015) <https://doi.org/10.4081/gh.2015.306>
30. DHS Program. Guide to DHS Statistics (DHS-8). StatCompiler. Rockville (MD): ICF; 2023. Available from: <https://www.dhsprogram.com/Data/Guide-to-DHS-Statistics/index.cfm>. Accessed June 2, 2025
31. Lutambi AM, Emidi B, Mbuya FG, Ryoba M, Sagamiko TD, Hugo AK, et al. (2025) Modelling the impact of climatic and environmental variables on malaria incidence in Tanzania: Implications for achieving the WHO's 2030 Targets. *PLOS Glob Public Health* 5(8): e0005075. <https://doi.org/10.1371/journal.pgph.0005075>
32. Chen Y. Spatial autocorrelation equation based on Moran's index. *Sci Rep.* 2023;13(1):19296. <https://doi.org/10.1038/s41598-023-45947-x>
33. Kleinschmidt, I., Bagayoko, M., Clarke, G. P., Craig, M. & Le Sueur, D. A spatial statistical approach to malaria mapping. *Int. J. Epidemiol.* 29(2), 355–361 (2000). <https://doi.org/10.1093/ije/29.2.355>
34. Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple and robust tests for spatial error components and spatial lag dependence. *Regional Science and Urban Economics*, 26(1), 77–104. [https://doi.org/10.1016/0166-0462\(95\)02111-6](https://doi.org/10.1016/0166-0462(95)02111-6)
35. Kim JH. Multicollinearity and misleading statistical results. *Korean J Anesthesiol.* 2019;72(6):558–69. <https://doi.org/10.4097/kja.19087> PMID: 3130469

36. Olela SO, Makokha GL, Obiero K. Spatiotemporal Variation of Malaria Transmission in Different Altitudes of Lower Lake Victoria Basin, Kenya. *Eur J Health Sci.* 2022;7(6):1–24. <https://doi.org/10.47672/ejhs.1277>
37. Rubuga FK, Moraga P, Ahmed A, Siddig E, Remera E, Moirano G. Spatio-temporal dynamics of malaria in Rwanda between 2012 and 2022: a demography-specific analysis. *Infect Dis Poverty.* 2024;13(1):67. <https://doi.org/10.1186/s40249-024-01237-w>
38. D, Birhanu Z, Negash A, Hawaria D, Yewhalaw D. Effects of rainfall, temperature and topography on malaria incidence in elimination targeted district of Ethiopia. *Malar J.* 2021;20(1):104. <https://doi.org/10.1186/s12936-021-03641-1>
39. kunlola OA, Oyeyemi OT. Spatio-temporal analysis of association between incidence of malaria and environmental predictors of malaria transmission in Nigeria. *Sci Rep.* 2019;9(1):17500. <https://doi.org/10.1038/s41598-019-53814-x> PMID: 31767899
40. Okunlola O, Oloja S, Ebiwonjumi A, Oyeyemi O. Vegetation index and livestock practices as predictors of malaria transmission in Nigeria. *Sci Rep.* 2024;14(1):9565. <https://doi.org/10.1038/s41598-024-60385-z> PMID: 38671079
41. Kigozi R, Zinszer K, Mpimbaza A, Sserwanga A, Kigozi SP, Kamya M. Assessing temporal associations between environmental factors and malaria morbidity at varying transmission settings in Uganda. *Malar J.* 2016;15(1):511. <https://doi.org/10.1186/s12936-016-1549-2> PMID: 27756304
42. Tam LT, Thinkhamrop K, Suttiaprapa S, Clements ACA, Wangdi K, Suwannatrai AT. Bayesian spatio-temporal modelling of environmental, climatic, and socio-economic influences on malaria in Central Vietnam. *Malar J.* 2024;23(1):258. <https://doi.org/10.1186/s12936-024-05074-y> PMID: 39182127
43. Ugwu CLJ, Zewotir T, Evaluating the Effects of Climate and Environmental Factors on Under-5 Children Malaria Spatial Distribution Using Generalized Additive Models (GAMs). *Journal of Epidemiology and Global Health*, Vol. 10(4); December (2020), pp. 304–314 DOI: <https://doi.org/10.2991/jeqh.k.200814.001>;
44. Regional data & trends briefing kit: World malaria report 2024 https://cdn.who.int/media/docs/default-source/malaria/world-malaria-reports/world-malaria-report-2024-regional-briefing-kiteng.pdf?sfvrsn=bceac4ae_9&download=true Access March 17, 2026
45. DHS Program/ICF. Protecting the privacy of DHS survey respondents. Rockville (MD): ICF; 2019. Available from: <https://dhsprogram.com/methodology/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm>. Accessed July 10, 2025

Figures

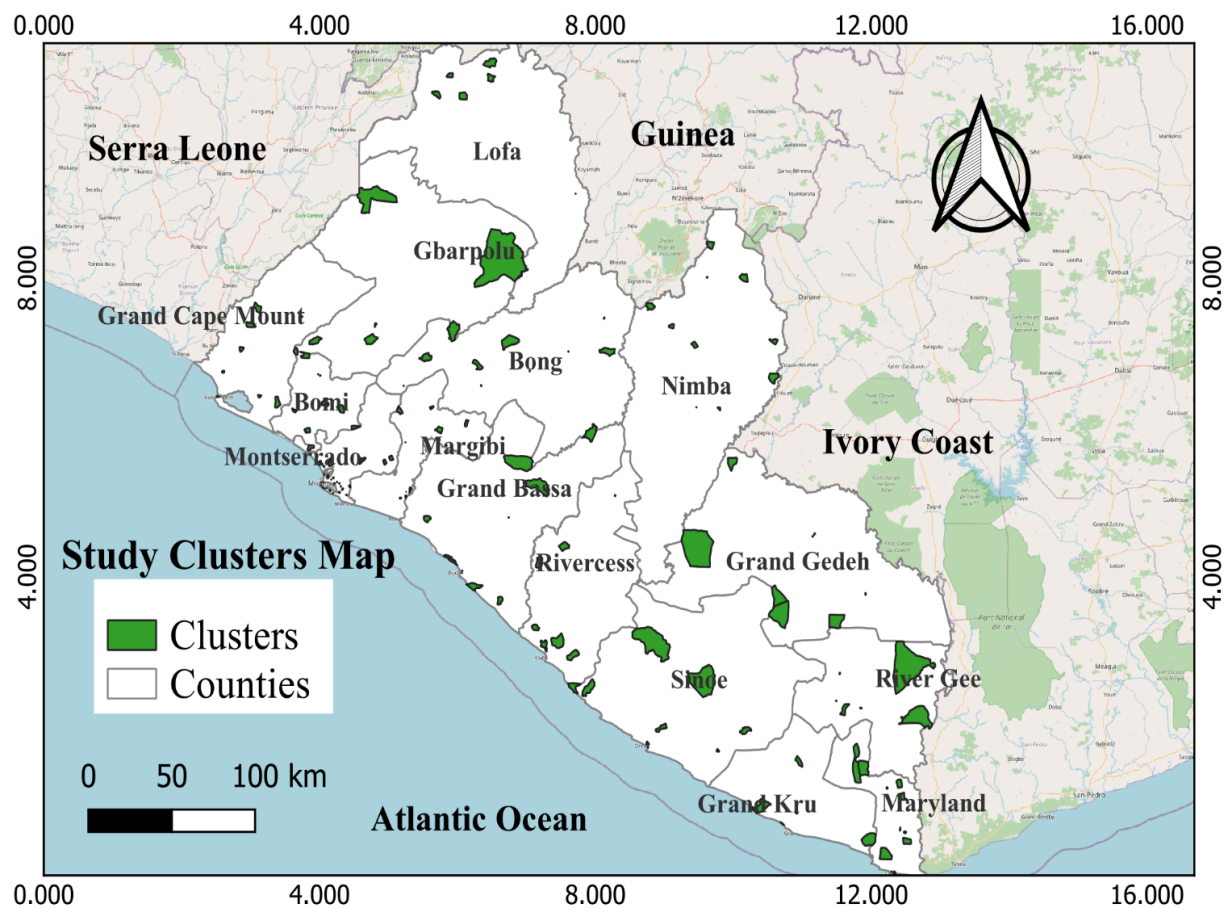


Figure 1

Map of Liberia showing the counties. This map was produced with QGIS using the Liberia's counties and LMIS 2022 shapefiles obtained from the Liberia Institute of Statistics and Geo- Information Services (LISGIS).

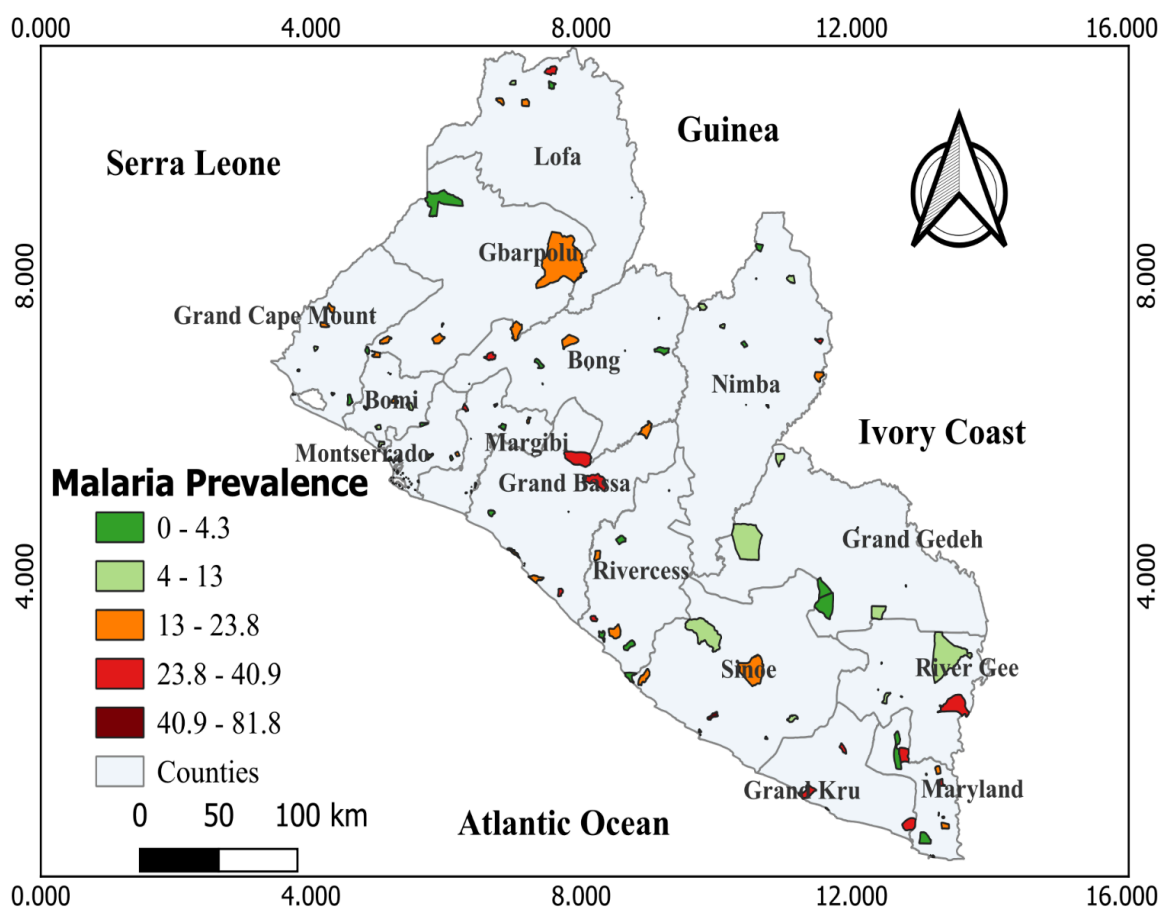


Figure 2

Spatial distribution of malaria prevalence in children under 5 years old in Liberia. Clusters are color-coded according to malaria prevalence ranges. This map was produced with QGIS using the Liberia's counties and LMIS 2022 clusters shapefiles obtained from the Liberia Institute of Statistics and Geo-Information Services (LISGIS).

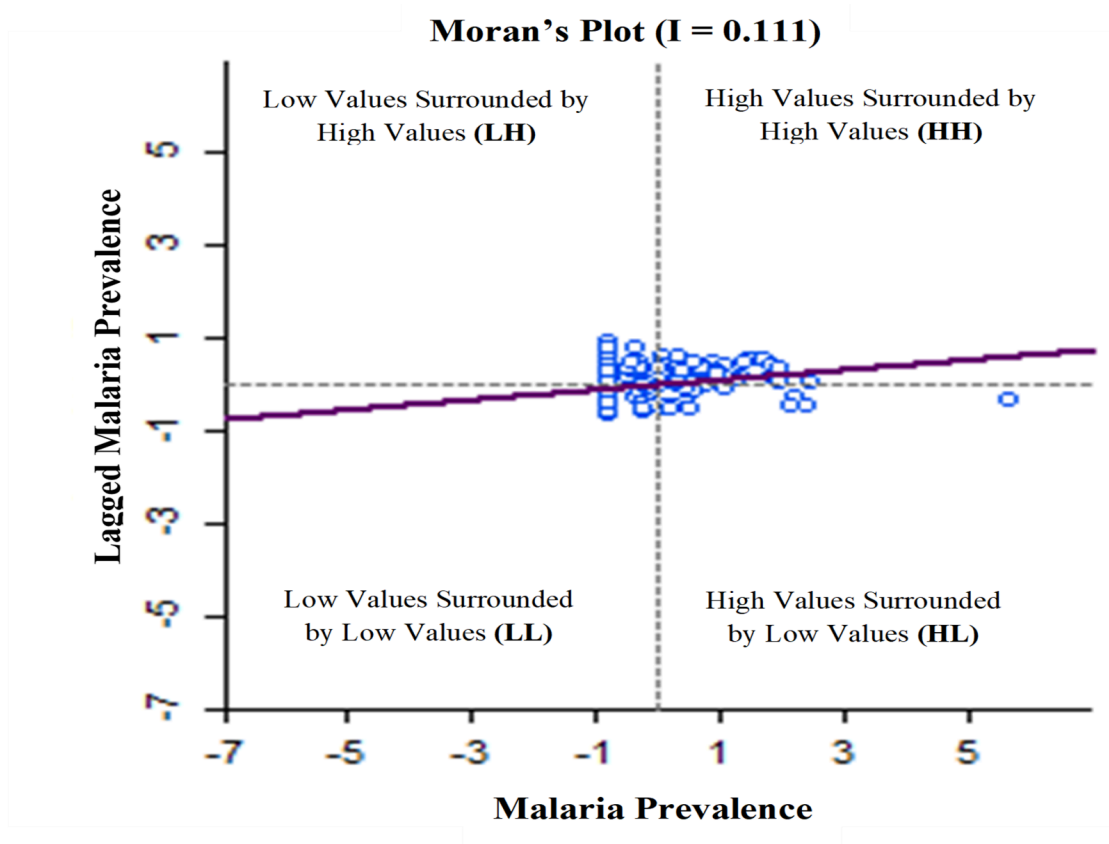


Figure 3

Moran's Scatter Plot Showing Moran's I values of Spatial Autocorrelation in Under-Five Malaria Prevalence at varying spatial lags

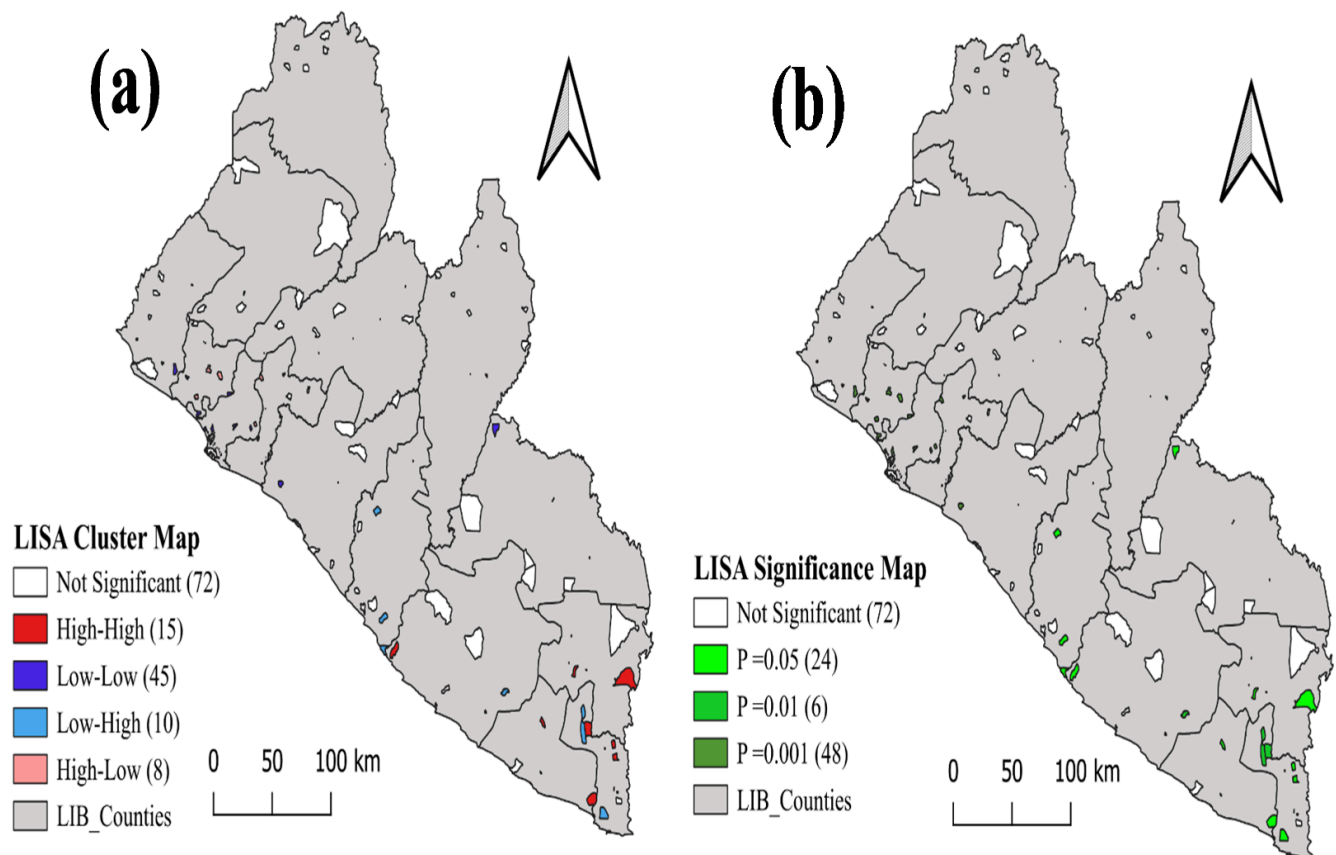


Figure 4

Shows (a) LISA Clusters map (b) and LISA significance map of Local Moran's I test Showing the hotspots and coldspots malaria locations in Liberia. This map was produced with GeoDa and QGIS using the Liberia's counties and LMIS 2022 clusters shapefiles obtained from the Liberia Institute of Statistics and Geo- Information Services (LISGIS)