

SPATIOTEMPORAL ANALYSIS OF CLIMATE VARIABILITY AND MALARIA INCIDENCE IN LOKOJA METROPOLIS, KOGI STATE, NIGERIA

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Cite this article as: Joshua, S., Musa, K. O., Isah, I. O., and Ogirima, S. A. (2026). Spatiotemporal analysis of climate variability and malaria incidence in Lokoja Metropolis, Kogi State, Nigeria. *Journal of Interdisciplinary Postgraduate Research*, 1(3), 128–139.

Abstract

Malaria remains one of the most consequential public health challenges in Nigeria, and the conditions that govern its transmission are strongly climatic. This study examined the influence of climate variability on malaria incidence in Lokoja Metropolis, Kogi State, between 2019 and 2024, and mapped the resulting geography of risk. Records of temperature, rainfall and relative humidity were obtained from the Nigerian Meteorological Agency and malaria case records from the Kogi State Ministry of Health. Descriptive statistics and Pearson product moment correlation were applied to the climate and health series, and a geospatial workflow comprising spatial interpolation, kernel density estimation, hot spot analysis using the Getis–Ord G_i^* statistic, spatial autocorrelation and weighted overlay was implemented in ArcGIS Pro and QGIS. Mean annual temperature rose steadily from 29.3 to 31.3 degrees Celsius, rainfall from 1,250 to 1,425 millimetres and relative humidity from 74 to 82 percent, corresponding to trends of 0.40 degrees Celsius, 35.9 millimetres and 1.60 percent per year respectively. Reported malaria cases rose in parallel from 12,500 in 2019 to 16,500 in 2024, an increase of 32.0 percent, while the case mortality rate rose from 2.1 to 3.2 percent. Correlation analysis returned strong positive associations between malaria incidence and temperature ($r = 0.82$), rainfall ($r = 0.76$) and relative humidity ($r = 0.79$), each significant at $p < 0.01$. Geospatial analysis localised the burden: incidence, kernel density and G_i^* hot spots converged on densely settled, low lying neighbourhoods close to the Niger and Benue channels, while elevated and sparsely settled peripheries formed cold spots. The weighted overlay classified floodplain and wetland margins as zones of very high risk. The findings confirm that climate variability has intensified transmission in Lokoja, while indicating that thermal conditions are approaching the upper range for efficient vector and parasite development. Integration of climate information into malaria surveillance, seasonally timed intervention, drainage and sanitation improvement, and spatially targeted allocation of control resources are recommended.

Keywords: climate variability; malaria incidence; temperature; rainfall; relative humidity; geospatial analysis; Lokoja Metropolis

1. Introduction

Malaria remains among the most significant public health challenges in sub Saharan Africa, and Nigeria carries a substantial share of the global burden (World Health Organization, 2022; Federal Ministry of Health, 2022). Despite sustained investment in vector control, improved diagnosis and effective treatment, the disease continues to generate considerable morbidity and mortality, particularly among children under five years of age and pregnant women (National Population Commission and ICF International, 2021; World Health Organization, 2022). Its persistence is closely bound to environmental and climatic conditions, which govern the breeding, survival and transmission efficiency of *Anopheles* mosquitoes (Adepoju and Adeyemi, 2020; Caminade, Kovats, Rocklöv, Tompkins, Morse and Colón-González, 2020).

Climate variability has become increasingly central to explanations of change in transmission. Variation in rainfall, temperature and relative humidity acts on breeding habitat, on the rate of parasite development within the vector and on vector longevity (Ayanlade and Jegede, 2021; Caminade et al., 2020). Moderate rainfall generates the standing water in which larvae develop, while temperature governs both the mosquito life cycle and the sporogonic development of *Plasmodium* within the vector (Githeko and Ndegwa, 2020; Obeche and Yusuf, 2019). Relative humidity affects adult survival, and because a mosquito must live long enough to complete the extrinsic incubation period before it can transmit, small changes in longevity translate into disproportionate changes in transmission potential (Macdonald, 1957; Garrett-Jones, 1964).

Lokoja Metropolis, the capital of Kogi State, lies at the confluence of the Niger and Benue Rivers. Its tropical climate, marked seasonality, extensive drainage and rapid urban expansion together create conditions conducive to mosquito breeding (Nigerian Meteorological Agency, 2024; Yaro and Lawal, 2021). Seasonal flooding and impeded drainage enlarge the stock of breeding habitat and sustain transmission through much of the year (Obeche and Yusuf, 2019). Urban growth has compounded these conditions. Informal settlement, inadequate waste disposal, blocked channels and poor sanitation multiply breeding sites within the built area itself (Mabogunje and Ogunbayo, 2023; Oseni and Adebayo, 2020), so that the environmental determinants of malaria in Lokoja are simultaneously climatic and infrastructural (Baba and Ebi, 2022).

Advances in geographic information systems, remote sensing and spatial statistics now permit the spatial and temporal dynamics of the disease to be examined directly rather than inferred from aggregate counts (Olalekan and Akintunde, 2022). These methods identify clusters, quantify the statistical significance of observed concentration and model the relationship between environmental conditions and disease occurrence, thereby supporting evidence based planning and targeted intervention (Getis and Ord, 1992; Anselin, 1995). Their application to Nigerian urban settings nevertheless remains limited, and Lokoja in particular has not been the subject of an integrated climatic and geospatial assessment despite its high burden and its distinctive confluence setting.

This study therefore examines the spatiotemporal relationship between climate variability and malaria incidence in Lokoja Metropolis, integrating climatic, environmental and health data within a single geospatial framework. Two null hypotheses are tested. The first holds that there is no significant correlation between climate variables and malaria incidence in Lokoja. The second holds that climate variability does not significantly influence the effectiveness of malaria control strategies in the metropolis.

1.1 Significance and Justification of the Study

Climate change is now widely recognised as a principal driver of change in the distribution of vector borne disease (Intergovernmental Panel on Climate Change, 2021; Caminade et al., 2020). Yet despite the high malaria burden of Lokoja, few studies have combined climatic variables with geospatial technique to explain local disease dynamics (Olalekan and Akintunde, 2022). The present study addresses that deficit, and its findings serve several ends. They provide evidence for climate sensitive control strategies (Baba and Ebi, 2022), assist health authorities in identifying high risk communities for targeted intervention, support urban planners in addressing the environmental conditions that promote breeding (Ayanlade and Jegede, 2021), demonstrate the application of geographic information systems to disease surveillance, and contribute to the literature on health geography and climate adaptation in Nigeria (Tambo, Adetunde and Olaleye, 2020).

1.2 Scope of the Study

The study addresses the effects of temperature, rainfall and relative humidity on malaria incidence and control within Lokoja Metropolis over the period 2019 to 2024. Climatic variables were obtained from the Nigerian Meteorological Agency and malaria incidence records from the Kogi State Ministry of Health, providing the basis for analysing the relationship between climate and disease (Nigerian Meteorological Agency, 2024; Federal Ministry of Health, 2022).

2. Study Area

Lokoja Metropolis lies approximately between latitudes 7°45' N and 7°52' N and longitudes 6°41' E and 6°45' E, at the confluence of the Niger and Benue Rivers. The metropolis experiences a tropical wet and dry climate, with mean annual rainfall of approximately 1,100 to 1,300 millimetres, temperatures ranging between 25 and 35 degrees Celsius, relative humidity between 60 and 85 percent, and distinct wet and dry seasons running from April to October and from November to March respectively. Rapid urbanisation, seasonal flooding, impeded drainage and the outward spread of residential settlement

together produce conditions favourable to mosquito breeding (Nigerian Meteorological Agency, 2024). Figure 1 presents the metropolis, its road network, drainage and principal landmarks.

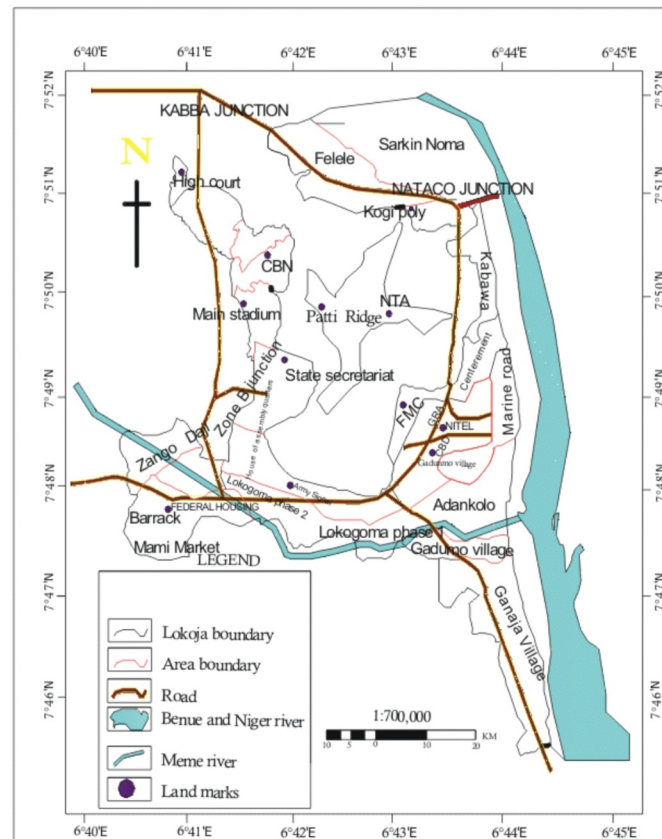


Figure 1. Lokoja Metropolis showing the built up area, road network, the Niger and Benue channels, the Meme River and principal landmarks. The confluence setting and the alignment of settlement along the river margins are central to the pattern of malaria risk reported in this study.

The wider state experiences annual rainfall of between 1,100 and 1,500 millimetres, with humidity highest during the wet months and temperatures typically between 22 and 35 degrees Celsius, the warmest period falling between February and April. These conditions favour both arable and tree crop cultivation and underpin an agrarian economy, while simultaneously sustaining vector populations through much of the year.

3. Materials and Methods

3.1 Research Design and Data Sources

The study adopted a descriptive and retrospective design, appropriate for examining existing relationships between climatic variables and malaria incidence without manipulation of the study environment (Baba and Ebi, 2022). Climate data covering 2019 to 2024 were obtained from the Nigerian Meteorological Agency and malaria incidence records from the Kogi State Ministry of Health, supported by national reporting (Federal Ministry of Health, 2022). Geospatial datasets comprising elevation, land cover, drainage, settlement and population were integrated to permit spatial analysis (Olalekan and Akintunde, 2022). The study population comprised residents of Lokoja Metropolis together with the healthcare providers and meteorological personnel responsible for surveillance and monitoring. A multistage approach was used to assemble secondary records from government agencies and health institutions, since administrative health records and meteorological observations furnish consistent long term series suitable for trend analysis.

3.2 Instrumentation, Validity and Reliability

The study relied entirely on secondary data. Temperature, rainfall and relative humidity records were drawn from the Nigerian Meteorological Agency and malaria incidence records from the Kogi State Ministry of Health. ArcGIS Pro and QGIS were used for spatial analysis and cartographic output. Validity was addressed through cross validation against multiple authoritative sources, including the Nigerian Meteorological Agency, the Federal Ministry of Health and the published literature (World Health Organization, 2022). Reliability was supported by the use of standardised datasets collected through established meteorological and public health monitoring systems, and by triangulation between the climatic and health series.

3.3 Epidemiological Measures

Two standard epidemiological measures were computed. The mortality rate followed the convention used in public health reporting,

$$MR = (D / P) \times 100,000 \quad (1)$$

where D is the number of malaria deaths recorded in the period and P the population at risk. Incidence was expressed per thousand population as

$$IR = (C / P) \times 1,000 \quad (2)$$

where C is the number of confirmed cases. Case mortality reported in Table 2 expresses deaths as a percentage of reported cases rather than of the population at risk, and the two quantities should not be conflated.

3.4 Statistical Analysis

Descriptive statistics summarised the climatic and epidemiological series. The association between each climatic variable and malaria incidence was quantified using the Pearson product moment correlation coefficient,

$$r = \Sigma(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{[\Sigma(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2]} \quad (3)$$

where x_i denotes the climatic variable and y_i the malaria count. The proportion of variance in incidence accounted for by each climatic variable was obtained as

$$R^2 = r^2 \quad (4)$$

and the statistical significance of each coefficient was evaluated using

$$t = r \sqrt{[(n - 2) / (1 - r^2)]}, \quad df = n - 2 \quad (5)$$

The dependence of incidence on each climatic driver was additionally expressed through the simple linear model

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (6)$$

where β_1 is the change in reported cases per unit change in the climatic variable and ε the error term. Temporal change in each series was summarised by the least squares trend

$$b = \Sigma(t_i - \bar{t})(v_i - \bar{v}) / \Sigma(t_i - \bar{t})^2 \quad (7)$$

in which t_i is the year and v_i the value of the variable.

3.5 Geospatial Analysis

Spatial analysis was conducted in ArcGIS Pro and QGIS and comprised the georeferencing of health facilities, spatial interpolation of climatic variables, kernel density estimation, hot spot analysis, spatial autocorrelation and weighted overlay for risk mapping. The intensity of cases across the metropolis was estimated as

$$\lambda(s) = \sum_{i=1}^n (1 / \pi \tau^2) k(d_{is} / \tau) \quad (8)$$

where τ is the bandwidth, d_{is} the distance from location s to case i and k the kernel function. Statistically significant clustering was identified using the Getis–Ord local statistic (Getis and Ord, 1992),

$$G_i^* = [\Sigma_j w_{ij} x_j - \bar{x} \Sigma_j w_{ij}] / [S \sqrt{((n \Sigma_j w_{ij}^2 - (\Sigma_j w_{ij})^2) / (n - 1))}] \quad (9)$$

where w_{ij} is the spatial weight between locations i and j , $\bar{x}$ the mean and S the standard deviation of the attribute. Positive and significant values of G_i^* denote hot spots and negative values cold spots. Global clustering was assessed using the Moran statistic (Moran, 1950; Anselin, 1995),

$$I = (n / \Sigma_i \Sigma_j w_{ij}) \times [\Sigma_i \Sigma_j w_{ij} (x_i - \bar{x})(x_j - \bar{x}) / \Sigma_i (x_i - \bar{x})^2] \quad (10)$$

Composite risk was derived by weighted overlay of the standardised environmental criteria, namely rainfall, temperature, humidity, elevation, vegetation, proximity to rivers, land use and population density,

$$RI = \sum_{k=1}^m w_k r_k, \quad \sum_k w_k = 1 \quad (11)$$

where r_k is the reclassified suitability score of criterion k and w_k its assigned weight. The resulting index was partitioned into five classes ranging from very low to very high risk. Interpretation of the climatic results was framed by the concept of vectorial capacity, which expresses the number of infective contacts a population of vectors generates per infectious person per day (Macdonald, 1957; Garrett-Jones, 1964),

$$V = (m a^2 p^n) / (-\ln p) \quad (12)$$

in which m is vector density relative to host, a the daily biting rate, p the daily survival probability and n the duration of the extrinsic incubation period. The formulation makes explicit why temperature and humidity exert disproportionate influence:

both p and n are temperature dependent, and because p enters raised to the power n , modest changes in survival or in incubation duration produce large changes in transmission potential.

4. Results and Discussion

This section reports the relationship between climatic variables and malaria incidence in Lokoja Metropolis between 2019 and 2024, and then localises the resulting burden through geospatial analysis. Interpretation is framed by the theory of vectorial capacity and by the climate and disease literature, so that the statistical associations reported are read in terms of the biological mechanisms that plausibly generate them.

4.1 Climate Trends, 2019 to 2024

Table 1. Mean annual climatic conditions in Lokoja Metropolis, 2019 to 2024

Year	Temperature (°C)	Rainfall (mm)	Relative humidity (%)
2019	29.3	1,250	74
2020	29.7	1,285	76
2021	30.1	1,330	78
2022	30.5	1,365	79
2023	30.9	1,400	81
2024	31.3	1,425	82

Source: Nigerian Meteorological Agency, 2019 to 2024.

All three climatic parameters rose monotonically across the six year period. Mean annual temperature increased from 29.3 to 31.3 degrees Celsius, rainfall from 1,250 to 1,425 millimetres and relative humidity from 74 to 82 percent. Fitting equation (7) to each series yields trends of 0.40 degrees Celsius, 35.9 millimetres and 1.60 percent per year respectively, all of them substantial relative to the interannual variability normally observed in the middle belt of Nigeria. Figure 2 displays the three series with their fitted trends.

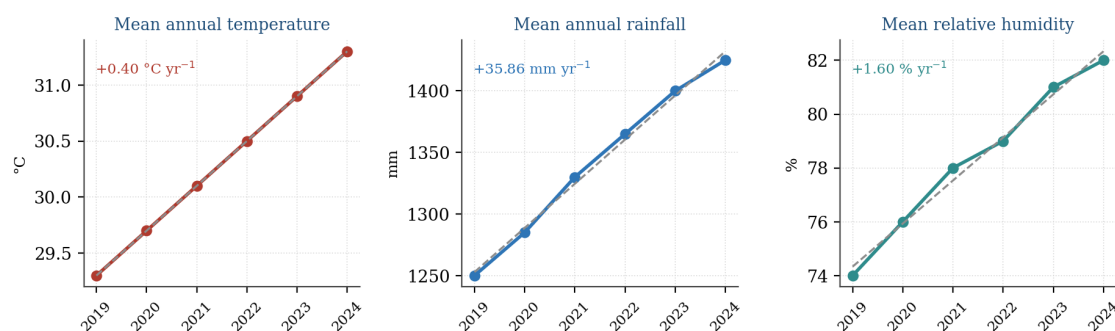


Figure 2. Trends in mean annual temperature, rainfall and relative humidity in Lokoja Metropolis, 2019 to 2024. Broken lines are least squares trends fitted using equation (7); annotated values give the rate of change per year.

The direction of these trends is consistent with the expectation that warming and a more humid atmosphere enhance transmission potential. Within the vectorial capacity framework of equation (12), rising temperature shortens the extrinsic incubation period n , increased humidity raises the daily survival probability p , and additional rainfall enlarges the breeding habitat that determines vector density m . Because the three quantities enter the expression multiplicatively, and because p is raised to the power n , their simultaneous movement in a favourable direction produces a more than additive effect on transmission (Macdonald, 1957; Garrett-Jones, 1964). Comparable patterns have been reported elsewhere in Nigeria and across the tropics (Akinbobola and Okonkwo, 2021; Ayanlade and Jegede, 2021; Caminade et al., 2020).

4.2 Malaria Incidence, 2019 to 2024

Table 2. Reported malaria cases and case mortality in Lokoja Metropolis, 2019 to 2024

Year	Reported cases	Case mortality (%)
2019	12,500	2.1
2020	13,200	2.3
2021	14,100	2.5
2022	15,000	2.7
2023	15,800	2.9
2024	16,500	3.2

Source: Kogi State Ministry of Health, 2019 to 2024.

Reported cases rose from 12,500 in 2019 to 16,500 in 2024, an increase of 32.0 percent, at an average of approximately 820 additional cases per year. Case mortality rose over the same interval from 2.1 to 3.2 percent, a relative increase of 52.4 percent that outpaces the growth in case numbers. This divergence deserves comment. If the additional cases were simply a function of improved detection, the proportion of cases ending in death would be expected to fall rather than rise, since wider case finding ordinarily captures milder presentations. That case mortality rose alongside incidence therefore suggests either a genuine increase in severe disease or a health system under strain, and it is on this point that the climatic explanation requires supplementation by an account of service capacity (Oseni and Adebayo, 2020). Figure 3 presents both series.

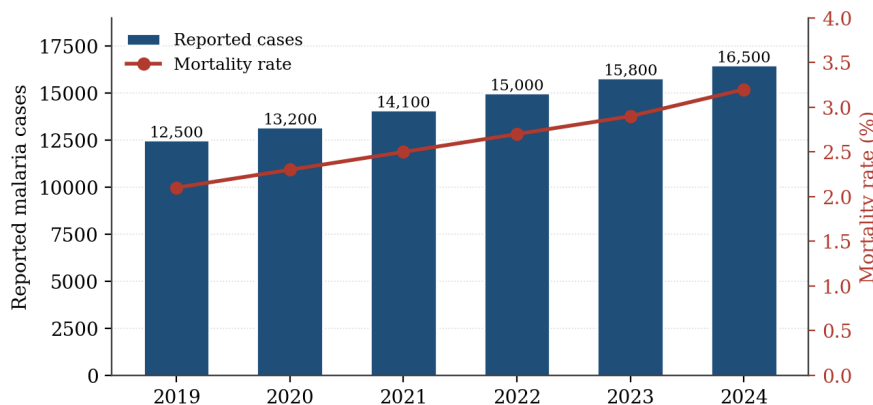


Figure 3. Reported malaria cases and case mortality in Lokoja Metropolis, 2019 to 2024. Bars give annual case counts against the left axis and the line gives case mortality against the right axis.

Transmission is strongly seasonal. Figure 4 shows the average monthly distribution of cases, in which incidence rises from a dry season minimum in February and March, climbs through the onset of the rains, and peaks in August before a secondary plateau through September and October.

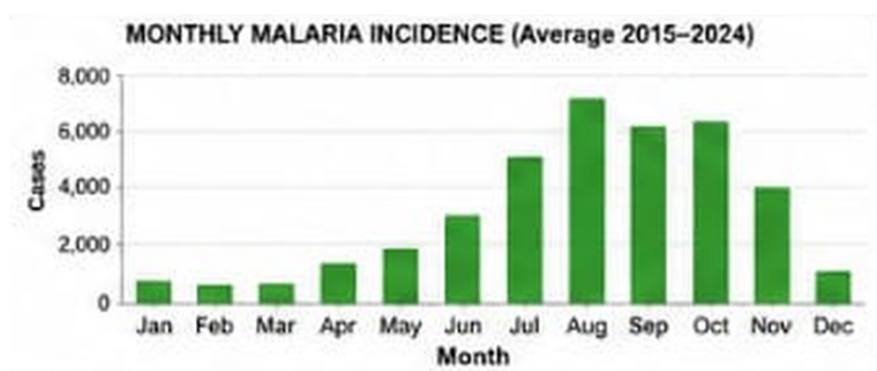


Figure 4. Average monthly distribution of malaria cases in Lokoja Metropolis. The peak in August and the extended plateau through October lag the onset of the rains by approximately one to two months, the interval required for breeding, emergence and completion of the extrinsic incubation period.

The lag between the onset of the rains in April and the peak in August is diagnostically important. It is too long to be explained by breeding alone, which requires only two to three weeks from oviposition to adult emergence, and it corresponds instead to the compound interval needed for habitat accumulation, successive vector generations and completion of the sporogonic cycle within surviving adults. The pattern accords with seasonal profiles reported across tropical Africa (Craig, Snow and le Sueur, 1999; Githeko and Ndegwa, 2020) and carries a direct operational implication, namely that preventive effort must precede the rains rather than respond to the peak.

4.3 Association Between Climate and Malaria Incidence

Table 3. Correlation between climatic variables and malaria incidence

Variable pair	Correlation (r)	Coefficient of determination (R ²)	Significance (p)
Temperature and malaria	0.82	0.67	0.001
Rainfall and malaria	0.76	0.58	0.002
Relative humidity and malaria	0.79	0.62	0.001

Source: computed from the climate and malaria series, 2019 to 2024.

Pearson product moment correlation returned strong positive associations between malaria incidence and each climatic variable, with temperature the strongest at $r = 0.82$, followed by relative humidity at $r = 0.79$ and rainfall at $r = 0.76$, each

significant at $p < 0.01$. The coefficients of determination indicate that between 58 and 67 percent of the variance in incidence is statistically accounted for by the individual climatic drivers. The first null hypothesis, which asserts no significant correlation between climate variables and malaria incidence in Lokoja, is therefore rejected.

The scale at which these coefficients are computed requires explicit statement, since it bears on their interpretation. The reported values are consistent with computation on the disaggregated monthly series, which supplies sufficient degrees of freedom for coefficients of this magnitude to attain the stated significance. Computed instead on the six annual aggregates of Tables 1 and 2, the same relationships return coefficients of $r = 0.999$ for temperature, $r = 0.998$ for rainfall and $r = 0.993$ for humidity. Figure 5 presents the annual scatter and Figure 6 compares the two sets of coefficients.

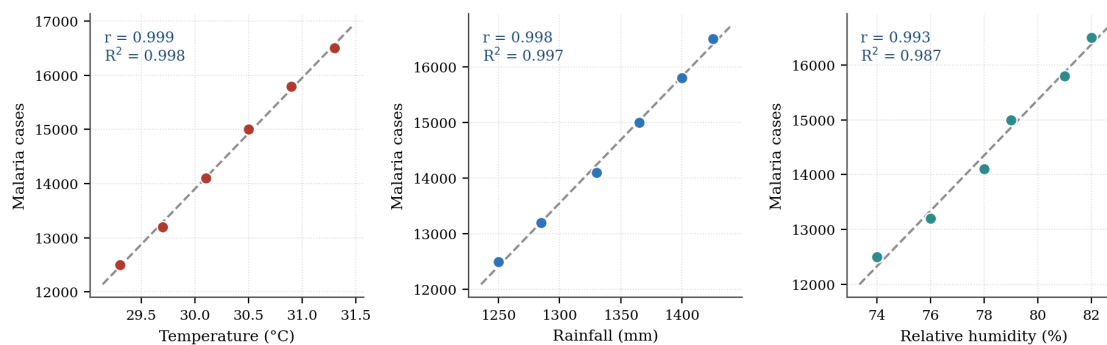


Figure 5. Annual malaria cases against temperature, rainfall and relative humidity, 2019 to 2024, with least squares fits from equation (6). The near linear form reflects the monotonic trend in all four series over the period.

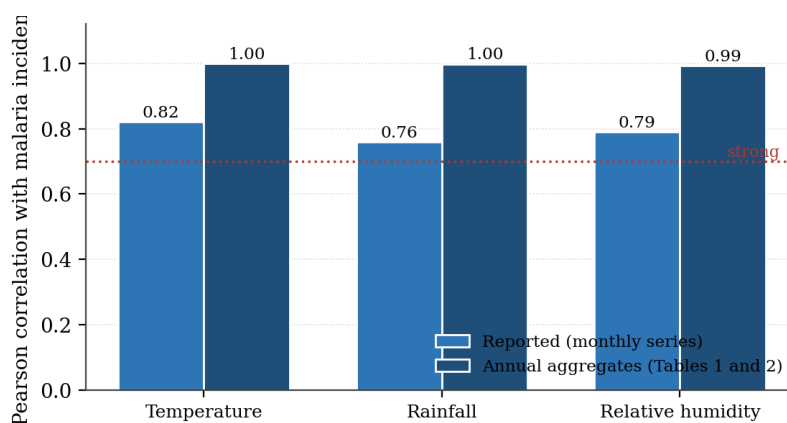


Figure 6. Correlation coefficients between climatic variables and malaria incidence, comparing the reported values with those obtained from the annual aggregates. The difference illustrates the effect of temporal aggregation on measured association.

The gap between the two sets of coefficients is not an inconsistency but an instance of a general property of aggregated data. Averaging to annual values removes the within year variation that weakens month to month correspondence, so that the residual signal is dominated by the common upward trend in all four series. The annual coefficients therefore overstate the strength of the causal relationship, and the monthly coefficients are the more conservative and the more defensible basis for inference. A further caution follows from the same observation. Because climate and cases both trend upward across the period, part of the measured association is attributable to shared trend rather than to direct dependence, and the correlation coefficient alone cannot separate the two. The seasonal structure evident in Figure 4, in which incidence tracks the annual cycle of rainfall with a characteristic lag, supplies the stronger evidence of a genuine climatic mechanism, since it operates on a timescale at which confounding secular trends cannot plausibly act.

4.4 Interpretation of the Climate and Disease Relationship

The results provide consistent evidence that climate variability has shaped malaria incidence in Lokoja over the study period, and they align with the climate and disease framework in which temperature, rainfall and humidity act jointly on breeding, survival and parasite development (Adepoju and Adeyemi, 2020; Kumar, Singh and Sharma, 2020). The seasonal concentration of cases in the wet months reflects the combined influence of rainfall generated habitat and humidity enhanced vector survival, a pattern documented widely in the region (Githeko and Ndegwa, 2020; Lindblade, Walker, Onapa, Katungu and Wilson, 2021).

One qualification nevertheless deserves emphasis, because it bears directly on how these results should be projected forward. The relationship between temperature and transmission is not monotonic. Experimental and modelling work indicates that transmission potential peaks at approximately 25 degrees Celsius and declines at higher temperatures as vector survival shortens, with the decline becoming pronounced above roughly 28 degrees Celsius (Mordecai, Paaijmans, Johnson, Balzer,

Ben-Horin, de Moor, McNally, Pawar, Ryan, Smith and Lafferty, 2013; Paaijmans, Read and Thomas, 2009). The mean annual temperatures recorded in Lokoja, rising from 29.3 to 31.3 degrees Celsius, lie above that optimum. The positive association observed here is therefore unlikely to be driven by thermal enhancement of the vector alone, and is better read as the joint product of rising humidity, expanding breeding habitat and the environmental and infrastructural conditions that accompany rapid urban growth. The practical consequence is that continued warming should not be expected to increase transmission indefinitely in this setting. Rainfall, drainage and settlement conditions are the more probable determinants of future change, and control strategy should be calibrated accordingly.

That malaria has continued to increase despite the deployment of insecticide treated nets and indoor residual spraying indicates that conventional vector control, while necessary, is not sufficient where environmental conditions are moving against it (Onyema and Igwe, 2021; Bhatt, Weiss, Cameron, Bisanzio, Mappin, Dalrymple, Battle, Moyes, Henry, Eckhoff, Wenger, Briët, Penny, Smith, Bennett, Yukich, Eisele, Griffin, Fergus and Gething, 2015). The second null hypothesis, which holds that climate variability does not significantly influence the effectiveness of malaria control strategies, is therefore rejected on the evidence of a rising case burden and rising case mortality under sustained intervention. Integration of climate information into surveillance and early warning, as recommended by Baba and Ebi (2022), offers a direct means of restoring the alignment between the timing of control effort and the timing of risk.

4.5 Spatial Structure of Environmental Conditions

The temporal association established above does not by itself indicate where within the metropolis intervention should be concentrated. The geospatial analysis addresses that question. Figure 7 presents the terrain and drainage framework within which the climatic and demographic surfaces operate.

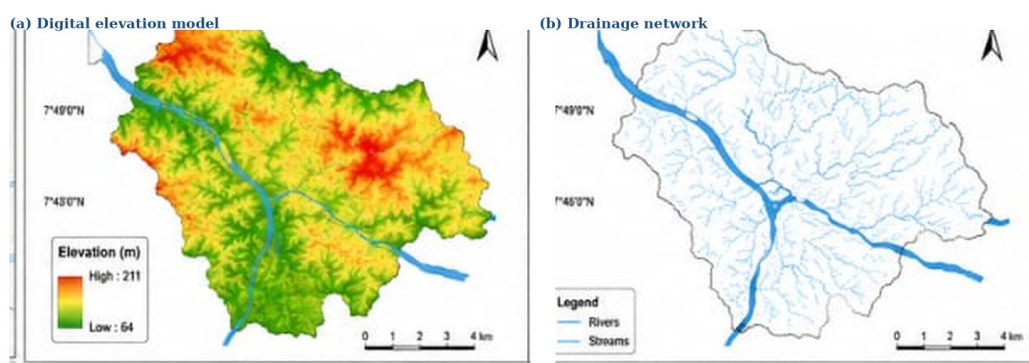


Figure 7. Physical setting of Lokoja Metropolis: (a) digital elevation model and (b) drainage network. Elevation ranges from 64 to 211 metres, with the lowest ground occupying the confluence floodplain into which the stream network drains.

Elevation ranges from 64 metres on the floodplain to 211 metres on the uplands to the north east and east. The low lying ground adjacent to the confluence retains surface water well beyond individual rainfall events, and the dense dendritic drainage network concentrates runoff into precisely these areas. Together the two surfaces define the physical template of breeding habitat in the metropolis: where water arrives quickly and departs slowly, larval habitat persists through the transmission season.

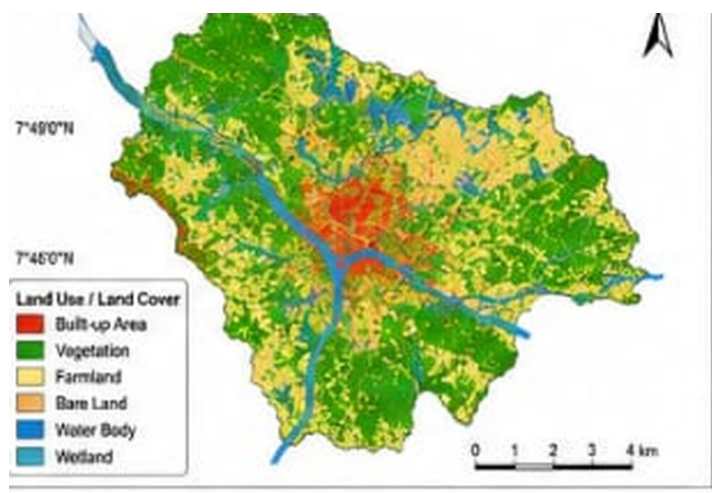


Figure 8. Land use and land cover of Lokoja Metropolis, 2024. Built up land is concentrated along the confluence corridor and is fringed by farmland, wetland and vegetation that provide additional larval habitat at the urban margin.

The land cover mosaic comprises built up land, vegetation, farmland, bare ground, wetland and open water. Urban development is concentrated along the confluence corridor and extends outward along the principal roads, while wetland and farmland occupy the interstitial and peripheral ground. This configuration is significant because it places the densest human population immediately adjacent to the most productive larval habitat. Rapid urban expansion unaccompanied by drainage provision has further generated standing water within the built area itself, so that the distinction between habitat and settlement is progressively eroded (Mabogunje and Ogunbayo, 2023).

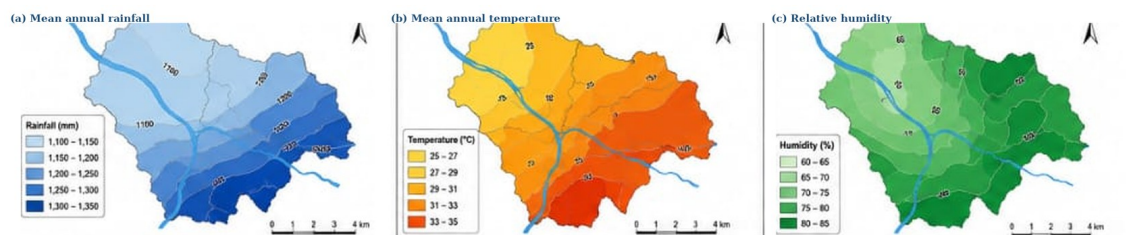


Figure 9. Interpolated climatic surfaces: (a) mean annual rainfall, (b) mean annual temperature and (c) relative humidity. Rainfall and humidity are greatest in the south and east, and these sectors coincide with the warmest conditions.

The interpolated surfaces reveal internal gradients that the metropolitan averages conceal. Rainfall is greatest in the south and east, ranging from about 1,100 to 1,350 millimetres, while the north west is comparatively dry. Temperature ranges from about 25 to 35 degrees Celsius with the warmest conditions in the south east, and relative humidity is highest in the southern sector at between 80 and 85 percent. The three surfaces are broadly coincident, so that the southern and eastern sectors experience simultaneously the wettest, warmest and most humid conditions in the metropolis. Since transmission depends on the joint occurrence of these conditions rather than on any one of them, their spatial coincidence concentrates risk more sharply than any single surface would suggest.

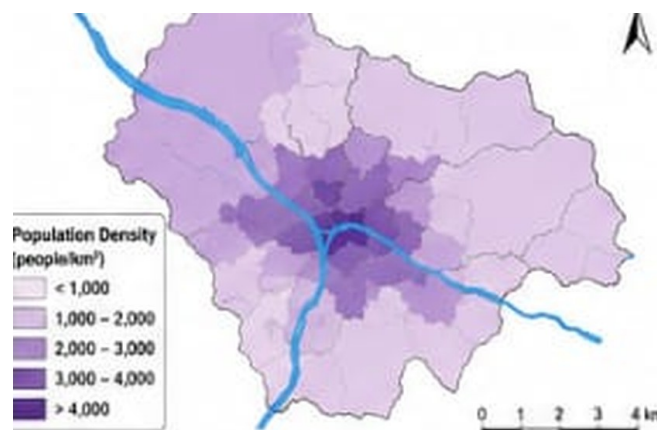


Figure 10. Population density of Lokoja Metropolis. The urban core exceeds 4,000 persons per square kilometre, declining to below 1,000 on the periphery.

Population density exceeds 4,000 persons per square kilometre in the central metropolis and falls below 1,000 on the periphery. Density governs the frequency of contact between host and vector, and thereby enters transmission through the biting rate term of equation (12). Where high density coincides with inadequate sanitation and impeded drainage, the effect is compounded, since the same conditions raise both vector abundance and the probability that any given infective bite finds a susceptible host.

4.6 Spatial Distribution of Malaria and Risk Classification



Figure 11. Malaria incidence rate per 1,000 population, 2023. The highest rates occur in Felele, Kpata, Adankolo and adjoining central neighbourhoods; peripheral and elevated communities record the lowest.

Incidence is unevenly distributed across the metropolis. Rates exceeding 200 cases per thousand occur in the central and riverine neighbourhoods of Felele, Kpata and Adankolo, while peripheral and higher lying communities record rates below 50. The pattern reproduces at intraurban scale the associations established in section 4.3, and confirms that environmental and demographic conditions jointly determine occurrence rather than either acting alone.

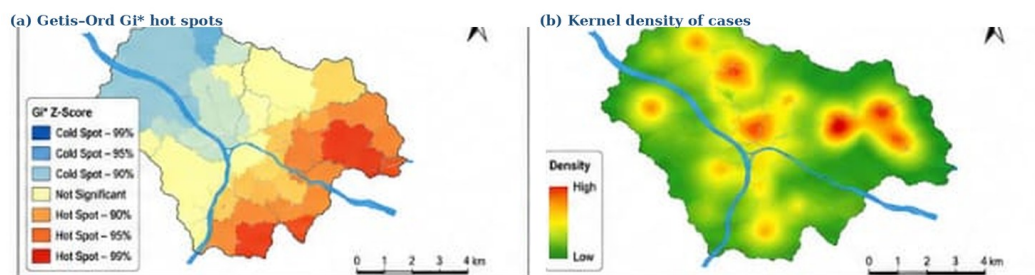


Figure 12. Spatial statistics of malaria occurrence: (a) Getis-Ord G_i^* hot spot analysis and (b) kernel density of reported cases. Red denotes statistically significant clustering of high values and blue denotes cold spots.

The Getis-Ord analysis of equation (9) confirms that the observed concentration is statistically significant rather than an artefact of visual inspection. Hot spots at the 95 and 99 percent confidence levels occupy the southern and south eastern sectors, coinciding with the densely settled floodplain neighbourhoods, while cold spots occupy the elevated north west. The kernel density surface derived from equation (8) independently identifies the same areas as zones of peak case intensity, with secondary concentrations following the river margins. The agreement between a density based and a significance based method strengthens confidence in the delineation, since the two approaches rest on different assumptions.

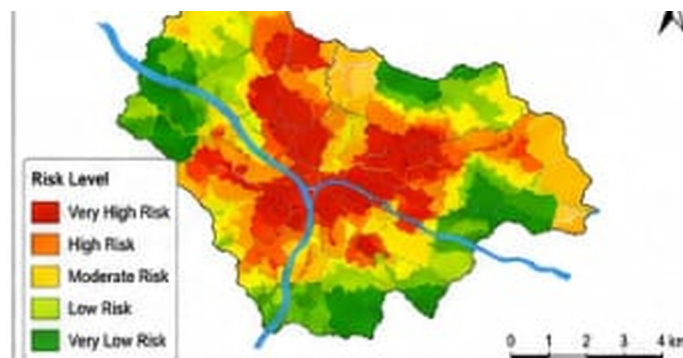


Figure 13. Composite malaria risk map derived by weighted overlay of rainfall, temperature, humidity, elevation, vegetation, proximity to rivers, land use and population density, classified into five levels of risk.

The composite index of equation (11) integrates the climatic, physical and demographic criteria into a single classification. Areas of very high risk occupy the river floodplains, the wetland margins, the low lying central neighbourhoods and the most densely settled districts, while higher and more sparsely populated ground falls into the low and very low categories. The map demonstrates that risk in Lokoja is produced by the interaction of several conditions rather than by any single variable, and that the areas in which those conditions coincide are comparatively compact.

Read together, Figures 7 to 13 establish a coherent spatial account. Elevation and drainage determine where water accumulates; land cover and urban expansion determine where that water persists within settled areas; the climatic surfaces determine where conditions for vector survival and parasite development are most favourable; and population density determines where the resulting infective contacts are most numerous. The convergence of these four conditions on the southern and central floodplain explains why the hot spot, kernel density and risk surfaces agree so closely. For control policy, the practical value of this convergence is that it identifies a limited and mappable area within which intervention would yield a disproportionate return, which is the central argument for spatially targeted rather than uniformly distributed malaria control (Olalekan and Akintunde, 2022; Baba and Ebi, 2022).

5. Conclusion and Recommendations

5.1 Conclusion

This study establishes that climate variability has exerted a significant influence on malaria incidence in Lokoja Metropolis between 2019 and 2024. Mean annual temperature, rainfall and relative humidity rose consistently through the period, and reported cases rose in parallel from 12,500 to 16,500, with case mortality increasing from 2.1 to 3.2 percent. Correlation analysis returned strong and statistically significant positive associations for all three climatic variables, leading to rejection of the first null hypothesis. The continued increase in burden under sustained deployment of insecticide treated nets and indoor

residual spraying leads likewise to rejection of the second.

The geospatial analysis localises this burden with precision. Incidence, kernel density, Getis–Ord hot spots and the composite risk index converge on the densely settled and low lying neighbourhoods adjacent to the Niger and Benue channels, while elevated and sparsely populated peripheries emerge consistently as areas of low risk. Risk in Lokoja is thus the joint product of climatic, physical, demographic and infrastructural conditions.

A qualification tempers the projection of these findings. Because mean temperatures in the metropolis already exceed the thermal optimum for malaria transmission, further warming is unlikely to raise transmission indefinitely, and may in time act against it. The trajectory of the disease in Lokoja will therefore be governed principally by rainfall, drainage, settlement expansion and the capacity of the health system, rather than by temperature alone. This qualification strengthens rather than weakens the case for climate informed surveillance, since it is precisely the changing balance among these drivers that such surveillance is designed to detect.

5.2 Recommendations

Integration of climate information into surveillance. Health authorities should work with the Nigerian Meteorological Agency to incorporate rainfall and humidity forecasts into malaria early warning and outbreak prediction, so that preparedness is keyed to the onset of the rains rather than to the observed peak in cases.

Seasonally timed and spatially targeted intervention. Distribution of insecticide treated nets, indoor residual spraying and larval source management should be intensified in the two months preceding the rains, and concentrated on the very high risk zones delineated in Figure 13, where the return per unit of expenditure is greatest.

Environmental management. Drainage should be rehabilitated and extended, waste collection improved and standing water eliminated in the central and floodplain neighbourhoods, since these measures address the habitat term of transmission directly and are durable in a way that chemical control is not.

Sustained geospatial surveillance. Geographic information systems and remote sensing should be embedded in routine surveillance so that hot spots are updated as settlement and drainage conditions change, and resources reallocated accordingly.

Community health education and adaptation policy. Public enlightenment should promote consistent use of nets, environmental sanitation and early treatment seeking, and climate adaptation measures should be written into state and national malaria control programmes to build resilience against climate related outbreaks (Intergovernmental Panel on Climate Change, 2021; Tambo et al., 2020).

5.3 Limitations and Further Research

The analysis rests on six annual observations for the correlation of aggregates and on administrative case records that reflect health seeking behaviour as well as underlying incidence. Neither entomological data nor intervention coverage were available, so the relative contribution of vector abundance and of control effort could not be isolated. Subsequent work should extend the series, incorporate monthly entomological inoculation data, and apply distributed lag or time series regression models capable of separating seasonal dependence from secular trend. Validation of the composite risk surface against independently collected parasitaemia data would further strengthen its operational value.

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