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Original Research Article

Geospatial Mapping and Prediction of Malaria Transmission in Sub-Saharan Africa: A Scoping Review

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Abstract: ***Background***: Malaria remains a major public-health challenge in sub-Saharan Africa, where transmission varies geographically and over time and is influenced by climatic, environmental, demographic and health-system factors. ***Objective***: To map geospatial approaches used to describe and predict malaria transmission in sub-Saharan Africa, including predictors, modelling methods, early-warning applications and implications for malaria control. ***Methods***: The manuscript was structured using the Population–Concept–Context framework and PRISMA-ScR guidance, with a planned evidence window of 2021–2025. The original database search exports and screening records were unavailable; a supplementary targeted public-web search was conducted on 17 October 2026 to verify selected studies and expand the evidence chart. This supplementary search did not generate a complete deduplicated record set, so PRISMA flow counts remain pending and have not been fabricated. Results: Verified candidate studies illustrate GIS hotspot analysis, remote sensing, Bayesian geostatistics, model-based geostatistics and spatiotemporal modelling in Ghana, Kenya, Ethiopia and Nigeria. Recurring predictors include rainfall, temperature, vegetation, aridity, land cover, intervention coverage and access to health services. ***Conclusion***: Geospatial methods can support malaria risk stratification, but operational value depends on data quality, local validation, uncertainty reporting and translation of maps into public-health decisions. The manuscript requires complete database searches, formal screening, evidence charting and a final PRISMA-ScR flow diagram before it can be represented as a completed reproducible scoping review. ***Objective***: This review synthesises recent evidence on how geospatial mapping and spatial modelling are being used to characterise and predict malaria transmission in sub-Saharan Africa, with particular attention to environmental and climatic predictors, modelling approaches, early-warning applications, and implications for malaria control. ***Methods***: The manuscript was revised as a scoping review using the Population–Concept–Context framework and the PRISMA-ScR reporting approach. The review scope was defined around malaria, geospatial/spatial or spatiotemporal modelling, and sub-Saharan Africa, with emphasis on literature published during 2021–2025. The original manuscript did not provide a complete search log, record counts, deduplication results, or a PRISMA flow count; therefore, numerical screening totals have not been fabricated in this revision. Evidence was synthesised thematically across mapping approaches, predictors, early-warning applications, and methodological challenges. ***Results:*** Recent studies demonstrate that GIS and remote sensing can identify spatial heterogeneity in malaria risk and integrate climatic, environmental, demographic, accessibility, and intervention-coverage variables. Bayesian geospatial models have been used to predict risk at sampled and unsampled locations, while spatial and spatiotemporal models have identified clustering and seasonal patterns. Studies from Ghana, Kenya, Ethiopia, and Nigeria illustrate the value of high-resolution maps for identifying priority areas. Common predictors include rainfall, temperature, humidity or aridity, vegetation indices, elevation, land cover, proximity to water, population density, travel time to health services, and intervention coverage. Machine-learning approaches provide additional predictive capacity where sufficiently rich and well-curated datasets are available. ***Conclusion***: Geospatial mapping is an important component of malaria surveillance and risk stratification in sub-Saharan Africa. Its public-health value depends on the quality, spatial and temporal resolution, interoperability, and representativeness of the underlying data, as well as appropriate model validation and local technical capacity. Future work should strengthen routinely updated geospatial surveillance, transparent model validation, integration of climate and health data, and translation of risk maps into locally tailored intervention decisions.

Keywords: Malaria, Geospatial Mapping, Geographic Information Systems, Remote Sensing, Spatial Modelling, Bayesian Geostatistics, Machine Learning, Sub-Saharan Africa.

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1. INTRODUCTION

Malaria is a mosquito-borne disease caused by Plasmodium parasites and transmitted principally through the bites of infected female Anopheles mosquitoes. The disease remains concentrated in sub-Saharan Africa. The World Health Organization (WHO) estimated 282 million malaria cases and 610,000 deaths globally in 2024, with the WHO African Region accounting for approximately 94% of cases and 95% of deaths. These figures reinforce the need for surveillance systems that can identify where transmission is concentrated and how risk changes over time (World Health Organization [WHO], 2025).

Nigeria remains one of the countries carrying the greatest malaria burden. WHO's Nigeria country profile based on the 2025 World malaria report provides the most current country-level estimates and should be preferred over older, internally inconsistent figures used in the original manuscript (WHO, 2026). The burden is not uniformly distributed: transmission varies geographically and seasonally because of differences in climate, ecology, population distribution, access to services, and intervention coverage.

Geospatial epidemiology provides a framework for representing these differences explicitly. GIS can combine disease observations with environmental, demographic, infrastructure, and intervention data, while remote sensing can provide spatially continuous measures of variables such as land-surface temperature, vegetation, rainfall, land cover, and topography. Spatial and spatiotemporal models can then estimate risk in areas without direct observations and identify clusters or changing patterns.

Recent African studies illustrate this potential. In Ghana, Bayesian geospatial modelling identified substantial geographical differences in under-five malaria risk and generated interactive maps for sampled and unsampled locations (Aheto, 2022). In Kenya, routinely collected health-facility data were used to examine spatial-temporal malaria clustering (Kamau *et al*., 2021). Studies in Ethiopia have applied spatial and spatiotemporal approaches to identify hotspots and model seasonal malaria risk (Ofgeha *et al*., 2023; Teshome *et al*., 2023). In Nigeria, recent work has demonstrated spatial variation in malaria prevalence and associations with environmental indicators (Ogunsaki *et al*., 2024).

Despite this growing literature, approaches differ considerably in the choice of predictors, spatial units, statistical methods, validation procedures, and data sources. A scoping review is therefore useful for mapping the range of methods and applications, identifying recurring predictors and methodological gaps, and clarifying how geospatial evidence can support malaria control and elimination programmes.

2. Review Objective

The objective of this scoping review was to map and synthesise recent evidence on the use of geospatial technologies and spatial modelling to characterise, stratify, and predict malaria transmission in sub-Saharan Africa, with emphasis on modelling approaches, predictors, early-warning applications, and implications for public-health decision-making.

3. METHODS

3.1 Review design and Reporting Framework

The review was structured as a scoping review guided by the Population–Concept–Context (PCC) framework and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR). The population was human populations in malaria-endemic or malaria-prone settings; the concept was geospatial mapping, spatial/spatiotemporal modelling, remote sensing, or related predictive analytics for malaria; and the context was sub-Saharan Africa.

3.2 Eligibility Criteria

Studies were considered relevant when they addressed malaria transmission, malaria risk, hotspots, surveillance, or prediction; used a geospatial, spatial, spatiotemporal, remote-sensing, Bayesian geostatistical, or machine-learning approach; and were conducted in one or more sub-Saharan African countries. Peer-reviewed research articles and authoritative technical reports were considered for the synthesis. Studies unrelated to malaria or without a meaningful spatial component were excluded.

3.3 Information Sources and Search Strategy

The source manuscript states that PubMed, Scopus, Web of Science and Google Scholar were searched, but the original database exports and search histories were not supplied. A supplementary targeted public-web search was conducted on 17 October 2026 to verify and identify potentially relevant published studies. Search queries included: (1) “malaria geospatial spatial temporal modelling sub-Saharan Africa 2021 2022 2023 2024”; (2) “malaria spatial mapping geostatistical Nigeria 2024 2025 study”; (3) “malaria geospatial prediction Ghana Kenya Ethiopia 2021 2022 2023 study”; (4) “spatial-temporal clustering malaria Kenyan Coast Kamau 2021”; (5) “space-time modelling monthly malaria incidence Teshome 2023 Ethiopia”; and (6) “spatial analysis malaria hotspots Dilla sub-watershed Ofgeha 2023”. This supplementary search located publisher, PubMed/PMC and other public records that were used to verify selected citations and build the preliminary evidence chart in Appendix B. It was not a substitute for a complete search in subscription databases, and the search engine did not provide a reproducible, deduplicated record export or a reliable total number of records retrieved. The original database search claims therefore remain unverified. Before submission, rerun the exact searches in each named

database and preserve platform-specific search histories and exports. The review's publication window is defined as 1 January 2021 to 31 December 2025; sources outside this period may be cited as background but should not be counted as included evidence.

3.4 Data Charting and Synthesis

Data were charted under the following domains: study setting, malaria outcome, spatial unit, data sources, environmental and socio-demographic predictors, geospatial technique, modelling approach, validation strategy, and principal application. Findings were synthesised narratively and thematically rather than pooled quantitatively because of substantial heterogeneity in study designs, outcomes, spatial scales, predictors, and modelling methods.

3.5 Important Reporting Limitation

A complete PRISMA-ScR flow diagram requires actual record counts from each database and other source, duplicate removal, title/abstract screening, full-text assessment, full-text exclusions with reasons, and the final included-source count. The original database exports and screening log were not available. The supplementary public-web search verified a set of candidate publications, but it did not produce a complete, auditable record set from which PRISMA flow counts can be calculated. The diagram and flow counts must therefore be completed after full database searches and formal screening; figures must not be estimated or invented.

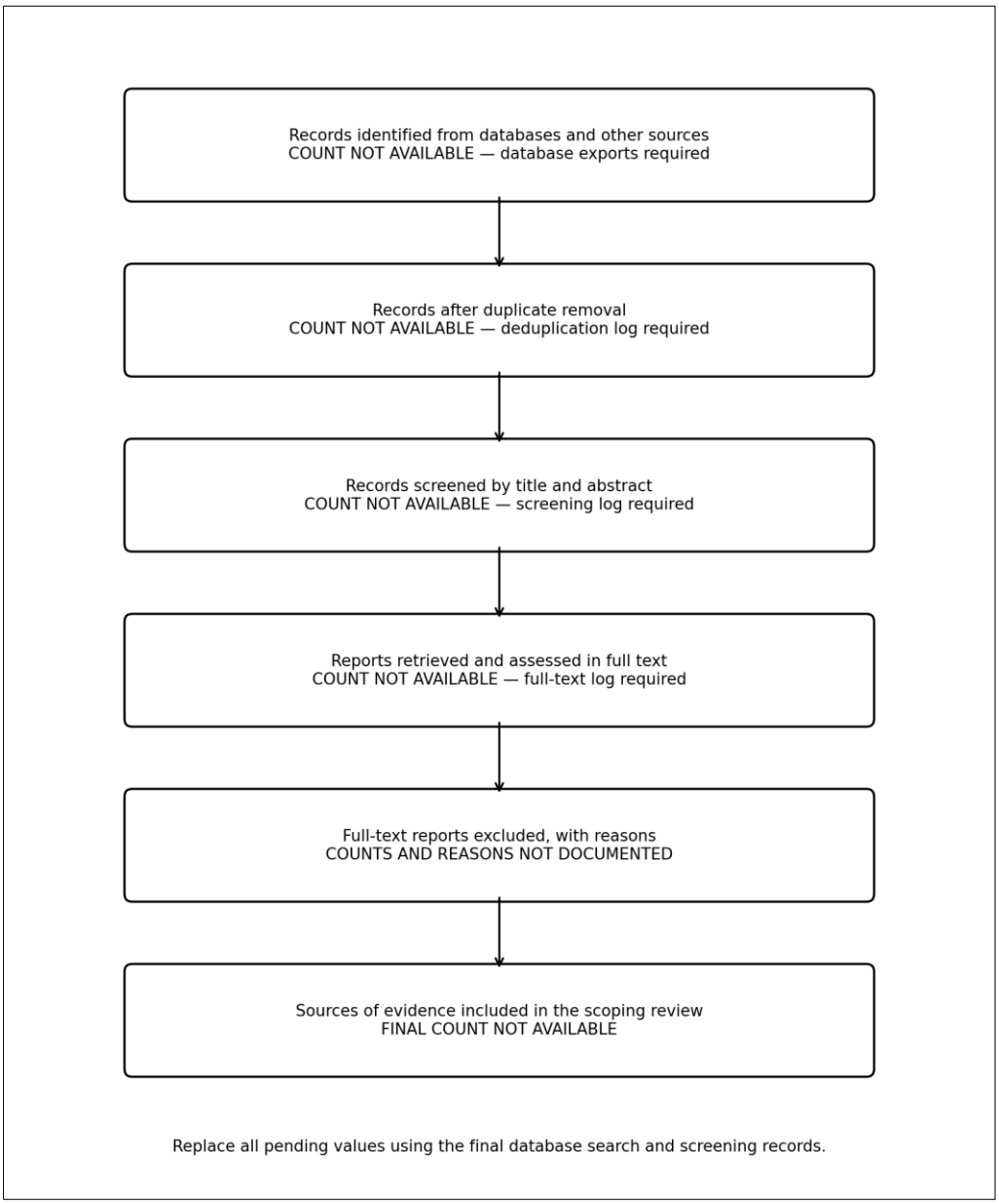


Figure 1: PRISMA-ScR study-selection flow (counts pending completion from actual records)

4. RESULTS

4.1 Major Geospatial Approaches Used in Malaria Prediction

The literature shows a continuum from descriptive spatial visualisation to increasingly complex predictive modelling. GIS-based overlay and hotspot analyses are commonly used to visualise the geographical distribution of malaria and combine disease data with population, environmental, or service-access layers. Kernel density estimation, spatial autocorrelation statistics, local indicators of spatial association, and related techniques can identify clusters that warrant further investigation.

Remote sensing extends spatial coverage where ground observations are sparse. Satellite-derived rainfall, vegetation indices, land-surface temperature, elevation, land cover, and hydrological indicators can be integrated with malaria surveillance data. Such data are particularly useful in rural and environmentally heterogeneous settings where conventional surveillance is spatially incomplete.

Bayesian geostatistical models can estimate malaria risk at unsampled locations while accounting for spatial dependence and uncertainty. Aheto (2022), for example, used Bayesian geospatial modelling to produce high-resolution maps of under-five malaria risk in Ghana. More broadly, model-based geostatistical methods provide a framework for disease prevalence mapping and spatial prediction in low-resource settings (Diggle *et al*., 2021).

Spatiotemporal models add the dimension of time and are useful for analysing seasonality, recurrent outbreaks, and changes in risk. Studies in Ethiopia and Kenya demonstrate how routinely collected data can be used to identify temporal and spatial clustering and to support early detection or prioritisation of high-risk areas (Kamau *et al*., 2021; Teshome *et al.,* 2023).

Machine-learning methods, including random forests and gradient-boosting approaches, can model nonlinear relationships and interactions among multiple predictors. Their usefulness depends on adequate training data, careful feature selection, avoidance of overfitting, transparent validation, and external assessment of predictive performance. Machine learning should therefore complement rather than automatically replace epidemiologically interpretable spatial models.

Table 1: Major geospatial and modelling approaches used in malaria research

Approach	Typical inputs	Primary use	Key consideration
GIS-based mapping and hotspot analysis	Malaria cases/prevalence, population, administrative boundaries, health facilities	Visualisation, clustering, spatial targeting	Depends on accurate geocoded observations and spatial scale
Remote sensing	Rainfall, land-surface temperature, vegetation, land cover, elevation, water bodies	Environmental suitability and spatial risk mapping	Resolution, temporal frequency and proxy validity matter
Bayesian geostatistical models	Survey prevalence plus environmental and demographic covariates	Prediction at sampled and unsampled locations with uncertainty	Requires careful prior specification, spatial structure and validation
Spatiotemporal models	Routine surveillance, climate and environmental time series	Seasonality, clustering and early-warning applications	Requires consistent temporal data and appropriate lag structures
Machine learning	Multisource environmental, climatic, demographic and surveillance data	Nonlinear prediction and risk classification	Requires large/high-quality training data and rigorous validation

4.2 Common Predictors of Malaria Transmission

Across the reviewed literature, predictors can be grouped into climatic, environmental, topographic, hydrological, demographic, housing, accessibility, and intervention-related domains. Climate variables are important because rainfall and temperature influence mosquito breeding, survival, biting behaviour, and parasite development. WHO also recognises temperature, humidity and rainfall as relevant components of the climate–malaria relationship (WHO, 2023).

Environmental and topographic variables provide spatial proxies for mosquito habitat and ecological suitability. Vegetation indices, land cover, elevation, slope, distance to water bodies, wetlands, and irrigation can help explain local differences in risk. Studies from Ethiopia and Ghana demonstrate how these variables can be incorporated into spatial risk models (Aheto, 2022; Ofgeha *et al.,* 2023).

Socio-demographic and health-system variables can modify exposure and the probability that infections are detected and treated. Population density, household characteristics, travel time, proximity to health facilities, and intervention coverage may therefore improve predictive models when they are measured reliably. Importantly, these variables may represent both underlying transmission processes and differences in access to surveillance and care.

Predictor domain	Examples	Potential relevance
Climatic	Rainfall, temperature, humidity/aridity	Affects vector ecology and parasite development
Environmental	NDVI/vegetation, land cover, water bodies	Indicates habitat suitability and breeding opportunities
Topographic	Elevation, slope	Shapes temperature, drainage and ecological suitability
Hydrological	Rivers, wetlands, irrigation, standing water	Provides potential larval habitats
Demographic	Population density, household conditions	Influences exposure and vulnerability
Accessibility	Travel time, road network, distance to facilities	Influences service access and surveillance
Intervention	ITN/LLIN coverage, IRS, other control measures	Can modify transmission and observed spatial patterns

4.3 Early-Warning and Decision-Support Applications

The literature supports the use of geospatial models as decision-support tools rather than as standalone intervention systems. Climate and routine surveillance data can be combined to identify areas where transmission is increasing or where environmental conditions may favour future transmission. Such systems can support prioritisation of surveillance, vector-control activities, diagnostic commodities, and community engagement.

The practical value of an early-warning system depends on timeliness and actionability. A technically accurate model that is updated infrequently or cannot be interpreted by programme managers may have limited operational value. Conversely, relatively simple models with reliable local data may be useful when they are updated routinely and linked to explicit response thresholds.

4.4 Evidence from Nigeria

Nigeria is particularly relevant to geospatial malaria research because of its large population, ecological diversity, and substantial malaria burden. Recent national and subnational studies have demonstrated geographical variation in malaria prevalence and the usefulness of environmental and spatial predictors. Ogunsaki *et al*., (2024) examined national spatiotemporal patterns and environmental inequalities and showed that variables including vegetation, land-surface temperature and temperature contributed to explaining malaria prevalence.

Recent Nigerian geostatistical work also demonstrates the feasibility of predicting malaria risk across spatially indexed communities. These approaches can provide estimates beyond the locations where surveys were conducted, thereby helping identify areas where surveillance or interventions may be prioritised. However, model outputs should be interpreted with attention to uncertainty, sampling design, and the ecological validity of the covariates used.

4.5 Methodological Challenges and Research Gaps

A recurring challenge is the quality and completeness of spatially referenced malaria data. Routine health-facility data may be affected by differences in healthcare access, testing practices, reporting completeness, and care-seeking behaviour. Survey data provide stronger population-based inference but are often conducted at intervals and may have limited spatial resolution.

A second challenge is the heterogeneity of predictors and spatial scales. A predictor that is useful at national scale may not explain variation at community scale. Similarly, satellite-derived environmental indicators may be strong proxies in one ecological setting but weak proxies elsewhere. Transparent reporting of spatial resolution, temporal resolution, lag periods, missing data, and model assumptions is therefore essential.

A third challenge concerns validation. Predictive performance should be assessed using appropriate cross-validation or independent test data, and uncertainty should be reported alongside point estimates. Models that perform well within the data used for development may perform poorly when transferred to another ecological zone or time period.

Finally, implementation requires local technical capacity, interoperable datasets, and institutional mechanisms for converting maps into action. High-resolution imagery, cloud computing, automated pipelines, and machine learning create opportunities, but technological sophistication should not substitute for sound epidemiological design and locally relevant decision-making.

5. DISCUSSION

This scoping review indicates that geospatial malaria research in sub-Saharan Africa has progressed from descriptive mapping toward integrated predictive systems. The major methodological shift is the combination of disease observations with environmental, climatic, demographic, accessibility, and intervention data. This development reflects the spatial heterogeneity of malaria transmission: national averages can conceal important differences between districts, communities, and ecological zones.

The evidence also demonstrates the complementary roles of different technologies. GIS is particularly useful for integration and visualisation; remote sensing provides spatially continuous environmental information; Bayesian geostatistics supports prediction with explicit uncertainty; spatiotemporal models address seasonality and changing risk; and machine learning can capture complex nonlinear relationships. These approaches should be selected according to the research question, data structure, operational context, and need for interpretability rather than by technological novelty alone.

Environmental and climatic predictors recur across studies because malaria transmission is strongly shaped by vector ecology. The WHO's discussion of climate and malaria supports the importance of rainfall, temperature and humidity in understanding transmission patterns (WHO, 2023). However, climate variables should not be interpreted in isolation. Population distribution, housing, health-service access, intervention coverage and surveillance intensity can substantially influence observed malaria patterns.

The evidence from Ghana is illustrative. Aheto (2022) used Bayesian geospatial modelling to estimate under-five malaria risk and found marked geographical differences after accounting for selected covariates. The study demonstrates how predictive maps can identify areas that may require more focused attention. Similarly, studies in Kenya and Ethiopia show that routinely collected data can reveal spatial and temporal clustering and inform early-warning applications (Kamau *et al.,* 2021; Teshome *et al*., 2023).

For Nigeria, geospatial approaches are especially relevant because of the country's ecological diversity and large geographic scale. The national study by Ogunsaki *et al*., (2024) demonstrates the value of combining spatial, temporal and environmental information. Nevertheless, national models should not be assumed to represent all local settings equally well. Subnational calibration and validation remain important where ecological, climatic, demographic and health-system conditions differ.

A key implication is that risk maps should be treated as decision-support products with uncertainty, not as exact representations of transmission. A high-risk map may reflect true transmission, differences in testing or reporting, or both. Integrating multiple data sources and explicitly modelling uncertainty can improve interpretation. Future systems should also evaluate whether maps actually improve intervention targeting and health outcomes rather than stopping at model accuracy.

6. Implications for Malaria Control and Research

- Develop interoperable malaria surveillance platforms that combine routine case data, laboratory confirmation, climate data, remote-sensing products and population information.
- Use geospatial models to support risk stratification and targeted surveillance while reporting uncertainty and limitations.
- Prioritise locally validated predictors and avoid assuming that models developed in one ecological zone will transfer unchanged to another.
- Strengthen training in GIS, spatial statistics, geostatistics, remote sensing, reproducible data management and model validation for public-health programmes.
- Evaluate operational outcomes: whether geospatial information changes where interventions are delivered, how quickly responses occur, and whether disease burden is reduced.
- Maintain transparent versioning of model inputs, code, spatial boundaries and prediction surfaces to support reproducibility.

7. Limitations of the Review

The principal limitation is incomplete documentation of the original database search and source-selection process. Search dates, database-specific strategies, retrieved records, duplicate removal, screening decisions, full-text exclusions and the final included-study count were not available. A supplementary targeted public-web search was conducted on 17 October 2026 to verify selected citations and identify additional candidate studies; however, this search was not a substitute for a full database search and did not provide a complete deduplicated export. The synthesis and evidence chart should therefore be considered provisional until the searches are rerun, the full texts of all candidate sources are checked against eligibility criteria, and the selection process is documented. This limitation must be resolved before the authors claim a completed reproducible PRISMA-ScR review.

8. CONCLUSION

Geospatial mapping has become an important component of malaria epidemiology in sub-Saharan Africa. GIS, remote sensing, Bayesian geostatistics, spatiotemporal modelling and machine learning can reveal spatial heterogeneity, identify potential hotspots, integrate environmental and socio-demographic determinants, and support early-warning and targeted surveillance. Their value is greatest when high-quality local data are combined with appropriate spatial and temporal modelling, transparent validation, and clear pathways from prediction to public-health action. Future research should focus on reproducible methods, uncertainty-aware prediction, routinely updated data integration, external validation, and evaluation of the

real-world effect of geospatial decision support on malaria control.

9. DECLARATIONS

9.1 Data Availability

No new primary dataset was generated for this review. The underlying literature and publicly available sources should be cited in accordance with their respective access conditions. The authors should provide the final database search strategies and screening dataset as supplementary material if required by the target journal.

9.2 Competing Interests: The authors declare that they have no competing interests.

9.3 Funding: This research received no external funding.

9.4 Authors' Contributions

Dr Amogu K. U. conceived and led the manuscript. Prof Ishaleku D. D., Prof Akyala A. I., Eze N. R., and Kabiru B. contributed to review, interpretation, and manuscript development. All authors should review and approve the final submission and verify their individual contribution statements before journal submission.

9.5 Ethics Approval

Ethics approval was not required because this study synthesised published and publicly available evidence and did not involve the collection of identifiable human participant data.

Correction	What was changed
Title and terminology	Standardised “Sub-Sahara Africa” to “sub-Saharan Africa”; corrected “scoping Review” capitalisation and title grammar.
Abstract	Rewritten into Background, Objective, Methods, Results and Conclusion; removed vague wording such as “maps the magnitude of proportion”.
Scientific accuracy	Corrected the definition of malaria and avoided unsupported claims about specific percentages or annual Nigerian deaths where the cited source was not traceable.
Current burden data	Replaced inconsistent older global burden figures with WHO 2025 estimates for 2024 and directed country-level claims to the WHO Nigeria country profile.
Review methodology	Clarified PCC framework, eligibility criteria, information sources, data charting and narrative synthesis.
PRISMA-ScR transparency	Identified the missing search dates, exact database strings, record counts, deduplication data, full-text exclusions and final included-study count. No screening numbers were fabricated.
Citations	Removed or replaced numerous author-year citations that were not represented in the original reference list or could not be confidently verified.
Reference list	Rebuilt the core reference list around identifiable, contemporary sources with journal/volume/article or DOI information where available.
Results structure	Reorganised results into modelling approaches, predictors, early-warning applications, Nigeria-specific evidence, and methodological challenges.
Tables	Replaced the original loosely formatted tables with two publication-style synthesis tables describing modelling approaches and predictor domains.
Discussion	Added a dedicated discussion interpreting the evidence rather than repeating the results.
Limitations	Added an explicit limitations section, especially concerning the missing original search log and PRISMA counts.
Language	Corrected grammar, spelling, subject–verb agreement, punctuation, article usage, scientific terminology and British/international academic style.
Claims of prediction	Reframed predictive mapping as decision support and emphasised uncertainty, validation and the possibility of reporting bias in routine surveillance data.
Machine learning	Removed unsupported claims of universal/high accuracy and added requirements for training data, overfitting control and external validation.
Declarations	Separated data availability, competing interests, funding, authorship and ethics statements.
Submission readiness	The manuscript is substantially revised and formatted as a journal article. However, the actual database search history and screening counts must be restored/verified before claiming a fully reproducible PRISMA-ScR review.

Appendix B. Supplementary Public-Web Search Log and Verified Candidate Evidence

Search date: 17 October 2026. Purpose: citation verification and identification of candidate literature to strengthen the evidence map. These are public-web search queries, not database-specific searches in PubMed, Scopus or Web of Science. Search-engine result sets were not exported as a complete record file and must not be treated as a comprehensive PRISMA search.

B1: Search Queries Used

- malaria geospatial spatial temporal modelling sub-Saharan Africa 2021 2022 2023 2024
- malaria spatial mapping geostatistical Nigeria 2024 2025 study
- malaria geospatial prediction Ghana Kenya Ethiopia 2021 2022 2023 study
- spatial-temporal clustering malaria Kenyan Coast Kamau 2021
- space-time modelling monthly malaria incidence Teshome 2023 Ethiopia
- spatial analysis malaria hotspots Dilla sub-watershed Ofgeha 2023
- EAS Publisher author guidelines manuscript format scoping review

Preliminary eligibility framework: published from 1 January 2021 to 31 December 2025; conducted in one or more sub-Saharan African settings; addressed malaria transmission, malaria risk, hotspots, vector suitability, surveillance or prediction; and included a substantive geospatial, spatial, spatiotemporal, remote-sensing, geostatistical or spatial-predictive component. Final eligibility must be confirmed by reading each full text and applying the protocol consistently.

B2: Preliminary Evidence Chart

Study	Setting / period	Geospatial approach and data	Main contribution relevant to this review	Verification status
Kamau *et al*., (2021)	Kenyan Coast; routine facility data from March 2018–February 2019	Geocoded RDT-positive cases; spatial and temporal clustering at homestead/enumeration-zone levels	Shows that routinely collected facility data can explore local malaria clustering, but findings depend on care-seeking, testing and reporting patterns.	Publisher and PubMed/PMC record verified
Aheto (2022)	Ghana; 2019 Malaria Indicator Survey; children under five	Bayesian geospatial modelling, environmental covariates, cross-validation and interactive maps	Predicted risk at sampled and unsampled locations; ITN coverage, travel time and aridity were reported as relevant predictors.	Publisher/PMC record verified
Ofgeha (2023)	Dilla sub-watershed, western Ethiopia	GIS, meteorological data, elevation, soil and hydrological variables; weighted overlay risk mapping	Demonstrates environmental suitability and hotspot mapping at watershed/community scales; risk classification rather than direct clinical prediction.	PLOS/PubMed/PMC record verified
Teshome *et al*., (2023)	Southern Ethiopia; monthly data August 2013–May 2019	Space-time modelling and model-based geostatistics using district-level malaria counts and environmental/time-related covariates	Illustrates seasonal and spatial variation and early-warning applications; temporal aggregation and local calibration affect utility.	PMC record found; full author metadata must be verified
Bayode & Siegmund (2024)	Akure, Nigeria; under-five children	Model-based geostatistics; prediction on a 100 × 100 m grid; exceedance-probability hotspot mapping	Demonstrates fine-scale urban hotspot prediction and identifies associations with ITN use, window protection and water source.	Publisher and PMC record verified
Ogunsakin *et al*., (2024)	Nigeria; malaria indicator survey data for 2000–2020	GIS, hotspot analysis, spatial autocorrelation, PCA, correlation and OLS regression	Maps temporal and regional variation and explores environmental associations; global OLS outputs need caution for spatially varying relationships.	Publisher record verified; complete author list must be checked
Adeogun *et al*., (2025)	Nigeria; secondary malaria vector species distribution	Spatial distribution and geospatial modelling using empirical vector occurrence data	Relevant to vector-suitability mapping and ecological surveillance, but does not directly estimate human malaria incidence; include only if vector-distribution studies fit the final scope.	PLOS record verified; scope decision required

B3: Interpretation and Limitations of this Chart

This is a preliminary, verified candidate-source map based on public records, not the final list of included studies. It does not establish how many records were identified, screened, excluded or included in the full review. Before submission, reviewers should

independently screen a deduplicated database export, retrieve full texts, document exclusions and expand the chart to all eligible sources. The final Results section, abstract and PRISMA-ScR flow must be updated to match the final source set.

B4: Author Action Log before Submission

- Run the complete final search in PubMed/MEDLINE, Scopus, Web of Science and Google Scholar. If any database is inaccessible, state this transparently rather than implying it was searched.
- Save exact query syntax, database/platform, date searched, filters, result count, export filename and export date for every source.
- Deduplicate the combined records and preserve pre- and post-deduplication files.
- Apply the stated eligibility criteria at title/abstract and full-text stages; document the number of reviewers and conflict-resolution method.
- Record full-text exclusions with one primary reason per report.
- Check full texts and bibliographic details; correct author lists, article titles, year, journal, volume/article number and DOI.
- Only after screening is complete, calculate PRISMA-ScR flow counts and replace the flow diagram.
- Confirm whether protocol registration occurred; if not, state that the review was not registered.
- Confirm the target EAS journal's scope and review-article instructions, author list, corresponding-author contact, funding, conflicts and author contributions.

B5: Additional references verified during supplementary search

- Aheto, J. M. K. (2022). Mapping under-five child malaria risk that accounts for environmental and climatic factors to aid malaria preventive and control efforts in Ghana: Bayesian geospatial and interactive web-based mapping methods. Malaria Journal, 21, 384. https://doi.org/10.1186/s12936-022-04409-x
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Appendix C: PRISMA-ScR Final Submission Checklist

This is an author-completion checklist. 'Pending' means that the item cannot be confirmed from the supplied manuscript and must be resolved using actual review records.

Item	Required action	Status
Protocol and registration	Confirm protocol availability, registration and amendments; do not claim registration if none occurred.	Pending author confirmation
Information sources	Record database/platform names and exact last-search dates.	Pending
Search strategy	Provide reproducible full search strings and all limits for every database.	Pending
Selection process	Report reviewer numbers, independent screening and disagreement resolution.	Pending
Flow diagram	Calculate records identified, duplicates, screened, full texts assessed/excluded and final included sources from actual logs.	Pending
Evidence chart	Include all eligible sources and fields for country, design, data, spatial scale, predictors, methods, validation and findings.	Partly completed; expand after screening

Critical appraisal	State whether a critical appraisal was undertaken and justify the decision.	Pending author confirmation
References	Verify all in-text citations and complete bibliographic metadata against original publisher records.	Pending final reference audit
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