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The Impact of Climate Variability on the Spatial Dynamics of Malaria in the Global South: A Systematic Review of Modelling Studies, with a Focus on Vulnerable Populations

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Abstract

Malaria remains one of the infectious diseases most strongly influenced by climate variability and climate change, with transmission dynamics closely linked to environmental conditions that affect both mosquito vectors and parasite development. Across malaria-endemic regions of the Global South, changes in temperature, rainfall patterns, humidity, and ecological suitability are altering malaria transmission, while rapid population growth, land-use change, and persistent socioeconomic inequalities may further increase the risk of disease resurgence and geographic expansion.

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to synthesize modelling studies published between 2010 and 2025 that examined the influence of climatic and environmental factors on malaria transmission in the Global South. Searches were conducted in PubMed, Embase, Scopus, and Web of Science. Eligible studies applied spatial, statistical, machine-learning, or hybrid modelling approaches to human malaria data and incorporated climatic or environmental predictors. Data were extracted on geographic setting, modelling methodology, climatic determinants, validation practices, and consideration of vulnerable populations.

A total of 39 studies met the inclusion criteria. Most studies were conducted in Africa (n = 26), followed by Asia (n = 11) and the Middle East and North Africa (n = 2). Mathematical and statistical models were the most frequently used approaches, followed by machine-learning and hybrid models. Temperature and rainfall emerged as the most consistently reported climatic drivers of malaria transmission, being examined in 92.3% and 76.9% of studies, respectively. Other important predictors included humidity, vegetation indices, elevation, and land surface temperature. Thirteen studies explicitly examined vulnerable populations, particularly children under five years of age, pregnant women, and low-income rural communities, highlighting the combined effects of climate variability, poverty, and limited access to healthcare. Machine-learning and hybrid approaches generally demonstrated superior predictive performance, whereas statistical models provided greater interpretability.

The evidence indicates that climate variability is a major determinant of malaria risk across the Global South. Future research should prioritize integrated modelling frameworks that combine climatic, environmental, and socioeconomic data to support climate-resilient malaria control, strengthen early-warning systems, and improve protection of vulnerable populations.

1. Introduction

Malaria remains one of the most severe global public health challenges, particularly affecting tropical and subtropical regions of the Global South [1]. The disease is transmitted through the bites of infected *Anopheles* mosquitoes carrying *Plasmodium* parasites, primarily *Plasmodium falciparum* and *Plasmodium vivax* [2]. Malaria continues to have devastating consequences for human health, livelihoods, and productivity at both national and international levels. In 2024, the World Health Organization (WHO) estimated 282 million malaria cases and 610,000 malaria-related deaths across 80 countries. The African Region accounted for 95% of all malaria cases (265 million) and deaths (579,000), while children under five years of age represented approximately 75% of all malaria deaths worldwide [2].

Climate variability has emerged as an important determinant of the spatial and temporal variability of malaria transmission. Changes in temperature, rainfall, and humidity directly influence mosquito survival, biting frequency, and the incubation period of *Plasmodium* parasites. Studies have shown that rising temperatures can expand vector habitats to higher altitudes and previously non-endemic regions, while excessive rainfall or extreme heat may suppress mosquito survival, highlighting the complex and non-linear relationship between climate and malaria transmission [3]. As climate variability intensifies, malaria transmission is expected to become increasingly uncertain, with a greater risk of outbreaks occurring in newly affected areas. Understanding these complex interactions between climate and malaria requires attention not only to environmental factors but also to the populations most vulnerable to exposure and severe disease outcomes [4].

The vulnerability of individuals and communities to malaria is not evenly distributed either across or within countries. Children, pregnant women, and low-income populations bear a disproportionate share of the burden, particularly in settings characterized by limited access to healthcare services, inadequate infrastructure, and poor housing conditions [5]. Focusing on these vulnerable populations is critically important, as it enables policymakers and public health practitioners to target malaria prevention and control interventions more effectively.

Modeling studies have substantially contributed to our understanding of the impact of climatic variables on malaria transmission [6]. Robust modeling frameworks are essential for elucidating the complex relationships between climate variability and malaria dynamics. Early statistical approaches, including linear regression and correlation analyses, provided valuable insights but were limited in several respects. In particular, these methods often assumed linear relationships and failed to account for spatial autocorrelation arising from geographically structured transmission processes [7]. More advanced approaches, including machine-learning techniques and Bayesian geostatistical models, offer greater flexibility and predictive performance, enabling the identification of malaria hotspots, the assessment of future risks under climate variability scenarios, and the development of early-warning systems for disease control and prevention [8].

Malaria transmission, climate variability, and human vulnerability are closely interconnected, collectively shaping how and where malaria affects populations across the Global South. Climate variability plays a major role by altering the environmental conditions that determine where *Anopheles* mosquitoes can survive and reproduce, thereby influencing the geographical distribution and seasonal dynamics of malaria outbreaks [9]. These environmental changes frequently intersect with existing social and economic inequalities, as disadvantaged communities often reside in areas that are disproportionately exposed to floods, droughts, and other climate-related hazards [10]. When combined with limited access to healthcare, sanitation, and vector-control measures, these factors further increase susceptibility to malaria infection and adverse outcomes [11]. Understanding how these environmental, social, and health-system factors interact is essential for building climate-resilient health systems and ensuring that malaria interventions reach the populations most in need [12].

Accordingly, this systematic review synthesizes evidence from spatial and machine-learning modeling studies published between 2010 and 2025, a period during which spatial modeling, remote sensing technologies, and machine-learning approaches became increasingly integrated into malaria research. The objectives of this review are threefold. First, to describe the geographic distribution of included studies and summarize their regional coverage across Africa, the Middle East and North Africa (MENA), and Asia. Second, to synthesize regional findings by examining what studies report regarding the relationships between climate variability and the spatial dynamics of malaria transmission. Third, to conduct a cross-regional comparison of modeling approaches, validation practices, and consideration of vulnerability factors, while explicitly identifying evidence gaps that are relevant for climate adaptation, public health planning, and malaria control strategies.

2. Materials and Methods

2.1 Search Strategy

Electronic databases, namely PubMed, Embase, Scopus, and Web of Science, were systematically searched for relevant publications published between 2010 and 2025. The search strategy was developed and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [13]. To ensure comprehensive coverage of the literature, Boolean operators (AND, OR) were used to combine key terms related to malaria, climate variability, spatial and geospatial analysis, and machine-learning approaches. Medical Subject Headings (MeSH) and database-specific controlled vocabularies, including Emtree terms, were incorporated where appropriate to improve search sensitivity and specificity. Searches were restricted to peer-reviewed journal articles published in English. All retrieved

citations were imported into EndNote X9 for reference management, and duplicate records were identified and removed prior to the screening process.

Table 1
Summary of the search queries used for each database during the systematic search.

Databases	Number of Retrieved Records	Search Terms
PubMed	111	See Table A1
Scopus	66	
Embase	82	
Web of Science	126	
Total	385	

2.2 Eligibility Criteria

The inclusion and exclusion criteria were developed using the PECOS (Population, Exposure, Comparison, Outcomes, and Study Design) framework. The Population of interest comprised human populations residing in malaria-endemic regions of the Global South. The Exposure was defined as climatic and environmental variables, including temperature, rainfall, humidity, vegetation indices, and related environmental factors, examined as determinants of malaria transmission. The Comparison component focused on differences in modeling approaches employed across studies, including statistical, spatial, geostatistical, and machine-learning methods. The Outcomes of interest included the spatial prediction or mapping of malaria risk, model performance and predictive accuracy, and the identification of climatic determinants associated with malaria transmission dynamics.

Regarding study design, eligible studies were peer-reviewed articles published in English that applied spatial, statistical, geostatistical, remote-sensing, or machine-learning modeling approaches to investigate the relationship between climatic factors and malaria transmission. Studies were excluded if they focused exclusively on mosquito vector ecology without incorporating human malaria data, did not include climatic or environmental variables as predictors, or lacked a modeling component relevant to malaria risk assessment. Non-peer-reviewed publications, conference abstracts, editorials, commentaries, dissertations, and gray literature were also excluded.

The review was restricted to studies published between 2010 and 2025. This period was selected because it corresponds to the rapid expansion and widespread application of spatial modeling, remote sensing technologies, geospatial analytics, and machine-learning techniques in malaria research, enabling increasingly sophisticated assessments of climate-sensitive malaria transmission and risk prediction.

2.3 Study Selection

The study selection process was conducted independently by two reviewers to ensure methodological rigor and minimize selection bias. All records retrieved from the database searches were imported into EndNote X9, and duplicate citations were identified and removed prior to screening. The reviewers initially screened the titles and abstracts of all unique records to assess their relevance to the review objectives. Studies deemed potentially eligible were subsequently retrieved for full-text assessment.

The predefined inclusion and exclusion criteria were applied consistently throughout both the title-and-abstract screening and full-text review stages. Any disagreements between the reviewers regarding study eligibility were resolved through discussion and consensus. When agreement could not be reached, a third reviewer was consulted to make the final determination. For studies whose eligibility could not be established based solely on the title and abstract, full-text articles were obtained and evaluated to ensure accurate inclusion decisions.

The entire study selection process was documented and reported in accordance with the PRISMA framework, and a PRISMA flow diagram was used to illustrate the identification, screening, eligibility assessment, and final inclusion of studies.

3. Results

A total of 385 records were identified through searches of four electronic databases: PubMed, Scopus, Embase, and Web of Science. Following the removal of 67 duplicate records, 318 unique studies remained for title and abstract screening. During this phase, 252 studies were excluded for not meeting the predefined inclusion criteria. The majority of excluded studies focused on diseases other than malaria (n = 142), followed by studies that did not include climatic or environmental variables (n = 45) and studies that did not apply spatial modeling approaches (n = 65).

Consequently, 66 articles were retrieved for full-text assessment. Following full-text review, 39 studies met all eligibility criteria and were included in the systematic review. The included studies represented a diverse range of modeling approaches, including Bayesian spatial and spatio-temporal models, geostatistical methods, and machine-learning algorithms. A summary of the study identification, screening, eligibility assessment, and inclusion process is provided in the PRISMA flow diagram (Fig. 1).

3.1 Studies by Geographic Region

The 39 studies included in this systematic review were unevenly distributed across geographic regions, reflecting both the global burden of malaria and regional differences in research capacity, data availability, and modeling priorities. Table 2 summarizes the geographic distribution of the included studies by region. The majority of studies were conducted in Africa, followed by Asia and the Middle East and North Africa (MENA). No eligible studies from Latin America and the Caribbean (LAC) met the inclusion criteria.

This geographic imbalance highlights important disparities in the application of spatial and machine-learning approaches to malaria research across the Global South. Given the substantial malaria burden borne by many African countries, the predominance of African studies is unsurprising. However, the limited representation of other regions, particularly LAC, suggests important gaps in the evidence base and underscores the need for broader geographical coverage to support climate-sensitive malaria surveillance, risk prediction, and control efforts.

Table 2
Geographic distribution of included studies (n = 39)

Region	Number of studies	Percentage (%)
Africa	26	66.6%
Asia	11	28.2%
Middle East & North Africa (MENA)	2	5.1%

3.1.1 Africa

Of the 39 studies included in this review, 26 (66.7%) were conducted in Africa, reflecting the region's disproportionate malaria burden as well as the increasing availability of high-resolution epidemiological, environmental, and climatic datasets for spatial analysis.

In East and Central Africa, studies conducted in Rwanda, Burundi, and the Democratic Republic of the Congo (DRC) applied spatial and machine-learning approaches to investigate the relationship between climate variability and malaria transmission. For example, a study in Rwanda employed a Geographically Weighted Random Forest (GWRF) model and

demonstrated that rainfall and land surface temperature (LST) were the most influential predictors of malaria incidence, while also revealing substantial spatial heterogeneity across the eastern and southern provinces [14]. Similarly, a study in Burundi utilized Bayesian generalized linear models and found that minimum temperature was strongly and positively associated with malaria incidence, whereas rainfall exhibited a more complex lagged effect on transmission dynamics [15].

In West Africa, studies from Benin, Ghana, Nigeria, and Togo consistently identified climatic and environmental determinants of malaria risk. In Ghana, Bayesian spatio-temporal models identified rainfall and maximum temperature as statistically significant predictors of malaria hotspots among children under five years of age [16]. In Nigeria, rainfall, humidity, and proximity to water bodies emerged as major determinants of malaria distribution, particularly in rural and agricultural settings [17, 18]. Studies conducted in Togo highlighted significant spatial clustering of malaria incidence, driven by mean temperature, precipitation, and vegetation indices [19, 20]. In Benin, a three-level Poisson mixed-effects model demonstrated that proximity to watercourses, soil characteristics, and vegetation density were key environmental determinants of malaria transmission and vector abundance [21]. More recent studies in Benin incorporated real-time meteorological data into support vector machine (SVM) algorithms, achieving predictive accuracies exceeding 80% and demonstrating the potential of machine-learning approaches for operational malaria forecasting [22].

In Southern Africa, studies from South Africa and Zimbabwe emphasized the climatic and environmental heterogeneity of malaria transmission. In Limpopo Province, rainfall and proximity to rivers were identified as significant predictors of malaria incidence [23]. Another South African study employed Seasonal Autoregressive Integrated Moving Average (SARIMA) models and found that the Normalized Difference Vegetation Index (NDVI), rainfall, and land surface temperature measured at a two-month lag were among the strongest predictors of malaria occurrence [24]. Similarly, studies from Zimbabwe identified temperature, rainfall, and relative humidity as the dominant climatic drivers of malaria risk, particularly in rural agricultural regions characterized by limited healthcare infrastructure and high environmental vulnerability [25].

Collectively, the African studies consistently identified temperature, rainfall, humidity, and vegetation-related indicators as key determinants of malaria transmission. At the same time, they demonstrated increasing recognition of spatial heterogeneity and growing adoption of advanced modeling approaches, including Bayesian geostatistical methods, spatially explicit machine-learning algorithms, and climate-informed forecasting frameworks. These findings underscore the importance of incorporating local environmental variability into malaria surveillance, risk mapping, and climate adaptation strategies across the continent.

Table 3
Modelling approaches, predictive performance, accuracy, and population studied for the Selected Studies in Africa.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
Ghana. [16]	Statistical/Spatiotemporal model using Bayesian hierarchical modelling. Spatial scale: 10 administrative regions of Ghana). Climate inputs: Median rainfall (mm/month), maximum temperature (°C), wet days (days/month), aridity index, and land surface temperature.	Validation: Internal validation using Deviance Information Criterion (DIC) and Watanabe Akaike Information Criterion (WAIC) to select best-fitting models. Metrics: Posterior means and 95% credible intervals for regression coefficients; DIC/WAIC for overall model evaluation. Sensitivity analyses: Compared Poisson vs Binomial likelihoods, Poisson produced better accuracy (DIC = 294.45 vs 295.48; WAIC = 320.6 vs 322.3). Tested models with and without covariates.	Inconsistencies in sampling design and differences in diagnostic methods (RDT and microscopy) across survey years. Bias and self-reporting errors and limited ability to assess causality or seasonality variations.	Under-five children.
Togo. [20]	Statistical/spatiotemporal time series model. Generalized Additive Models (GAMs) and Generalized Additive Mixed Models (GAMMs) with negative binomial distribution to account for overdispersion. Spatial scale: National, across all 40 districts. Climate inputs: total precipitation, rainy days, mean/min/max temperature, mean/min/max wind speed, relative humidity, Normalized Difference Vegetation Index (NDVI, 1 km resolution).	Validation approach: Internal, split by training/testing years. Model training used data from 2013 to 2016, with 2017 reserved for validation. The best-fitting models, mainly from the statistical approach, explained between 41% and 82% of the deviance during training, indicating good internal fit. However, predictive accuracy during testing was weaker, with mean absolute errors and percentage prediction errors varying widely across districts and target groups (up to ± 40% in children and over ± 100% in pregnant women).	Routine NMCP surveillance data, underreporting and missing values (e.g., Kpendjal and Oti in 2016). Excluded non-environmental factors (interventions, bed-net coverage, socioeconomic data).	Children < 5 years old, children ≥ 5 years old and adults, and pregnant women.
Global (focus on Africa for validation). [26]	Mechanistic transmission model incorporating climatic drivers. Three model: (1) Temperature only, (2) Temperature and Humidity, (3) Temperature, Humidity and Rainfall. Spatial scale: Global grid (10 km resolution). Climate input data: Temperature, relative humidity, rainfall (mm/day), and evaporation from ERA5-Land reanalysis (March 2022-May 2023).	Validation: Comparison with Malaria Atlas Project (MAP) prevalence data for Africa. Metric: Spearman correlation. Uncertainty & Sensitivity: Qualitative; uncertainty in data and model structure noted; improvements suggested through dynamic coupling with population and intervention data.	No incorporation of future environmental change or climate projections. A suitability index for *Anopheles gambiae* on a global scale has been considered, however this species largely only exists in Africa.	General population

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
Burundi. [15]	Bayesian statistical modelling combining Generalized Linear Models (GLM) and Generalized Additive Mixed Models (GAMM). Spatial scale: National coverage, 17 provinces of Burundi (area: 27,834 km²). Climate input data: Monthly precipitation, average of maximum temperature, average of minimum temperature, average of maximum humidity and average of minimum humidity, from the Geographic Institute of Burundi (IGEBU), 1996–2007.	Minimum temperature strongly and positively associated with malaria incidence, rainfall and maximum temperature showed negative effects. Model outputs were statistically consistent across both GLM and GAMM. Validation: Internal statistical validation using Bayesian inference. Model comparison performed using Akaike Information Criterion (AIC). Metric: Regression parameter significance (95% credible intervals) and AIC to assess model fit. Sensitivity analyses: Prior sensitivity analysis (hyperparameters) showed no major change in parameter estimates, confirming model robustness.	Only climate variables included; no socioeconomic, healthcare, or intervention factors considered. Missing meteorological data for 3 provinces, filled using kriging and nearest-neighbor interpolation.	General population
Zimbabwe. [25]	Hybrid multi-method framework combining (i) GIS-based spatial epidemiology (overlay analysis, Moran's I, Getis-Ord Gi*, spatial linear regression), (ii) statistical analysis of case-based surveillance data, and (iii) a mechanistic SEIRS transmission model integrated with GIS (SEIRS–GIS). Climate-driven simulations using historical data (2003–2023) and future SSP2-4.5 and SSP3-7.0 scenarios at sub-district scale.	validation includes split-sample temporal validation (training 2003–2015; testing 2016–2023), comparison of predicted verses observed incidence, and use of RMSE, AIC, and BIC for accuracy and calibration. Sensitivity analysis planned for key epidemiological and climate parameters; scenario uncertainty addressed via multiple SSP pathways.	Predictive accuracy untested. Incomplete and inconsistent retrospective surveillance and climate data (addressed via imputation and bias correction), uncertainty in climate projections, simplifying assumptions in the SEIRS model, and possible underrepresentation of intervention dynamics and behavioural factors despite multi-method design.	Entire population of Mberengwa District

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
Gambia. [27]	Supervised machine-learning classification models (C5.0 decision tree, XGBoost, random forest, ANN, SVM, KNN, logistic regression) to predict district-level monthly malaria outbreaks nationwide. Climate inputs include minimum and maximum temperature, rainfall, and relative humidity, combined with non-climatic predictors. National spatial scale (43 districts), 2013–2021.	Strong internal predictive performance on held-out testing data. Best models: C5.0 decision tree and XGBoost (testing accuracy 93.3%, sensitivity 96.7%, specificity 71.6%). Random forest: testing accuracy 91.5%, sensitivity 95.4%, specificity 65.1%. Lowest performer: SVM linear (testing accuracy 84.8%, specificity 44.7%).	Missing climate data imputed using monthly means across years, potentially smoothing extremes. No external validation beyond internal train-test split, non-climatic intervention variables acknowledged as important but not included.	General population
Zambia. [28]	Statistical/Spatiotemporal modelling using Bayesian hierarchical models and Generalized Linear Mixed Models (GLMM) with Poisson likelihood and Conditional Autoregressive (CAR) priors. Spatial scale: District-level (72 districts of Zambia), analyzed over 17 years (2000–2016). Climate inputs: Mean, maximum, and minimum temperature, diurnal temperature range (DTR), mean and maximum rainfall (mm), Normalized Difference Vegetation Index (NDVI).	Temperature, rainfall and NDVI predicted malaria incidence more accurately than intervention data (LLIN, IRS). Maximum temperature, minimum temperature, diurnal temperature range (DTR), and mean rainfall were the strongest climatic predictors. Validation: Internal validation only, model comparison based on DIC, WAIC, and log-likelihood criteria to evaluate predictive accuracy across models (environmental, intervention and combined). Sensitivity analyses: Compared model families, Poisson and Negative Binomial likelihoods and different variable subsets (intervention-only and environmental-only). Environmental-only model consistently showed stronger associations	The study assumes uniform climatic conditions within districts, which may overlook localized microclimatic variations that influence malaria transmission dynamics. Data quality and underreporting in early years prior to 2010.	Children under 5 years and population aged ≥ 5 years.
Sub-Saharan Africa. [29]	Hybrid: (i) machine learning (XGBoost (ii) GIS-based spatial autocorrelation analysis (global Moran's I; LISA clusters) (iii) Bayesian regression and spatial heterogeneity modelling. Spatial scale: multi-country regional (Sub-Saharan Africa), with country-level annual WHO data (2000–2022) and grid/raster MAP layers (2010–2022). Climate inputs: air temperature, precipitation,	Internal validation via cross-validation: machine learning reported higher goodness-of-fit than multiple linear regression. Spatial robustness tested by re-estimating Moran's I with an alternative KNN weight matrix (autocorrelation remained significant, $p < 0.01$).	Underreporting and variable surveillance coverage may bias trends and spatial clustering. Uses annual meteorological and malaria outcomes, which may miss lagged and localized climate effects.	General population

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	relative humidity, wind speed, wind direction.			
Togo. [19]	Statistical and spatial regression models, including Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM). Spatial autocorrelation assessed using Global Moran's I and LISA hotspot analysis. Climate inputs: mean temperature, rainfall, precipitation seasonality, and aridity index, combined with environmental variables (vegetation index, proximity to water bodies, altitude) and population density.	Model performance evaluated through model fit and spatial diagnostics. Spatial dependence confirmed Global Moran's I significant. Spatial Lag Model provided best fit (lowest AIC; highest adjusted R^2), outperforming non-spatial Ordinary Least Squares models. Uncertainty assessed via coefficient significance and comparison across model structures rather than probabilistic intervals.	Use of ecological regression assumes stable exposure outcome relationships and may not capture non-linear or lagged climate effects. Incidence estimates derived from linked survey and routine data may introduce spatial misclassification.	Children under 5 years of age
Benin. [22]	Machine-learning early warning model support vector machine. Spatial scale: sub-national (districts within 3 northern provinces). Climate input data: monthly temperature (mean/min/max), relative humidity (mean/min/max), rainfall/precipitation, and wind speed.	Internal validation using random split: 75% train, 15% test/validation, 15% calibration. Performance metrics include RMSE, MSE, MAE, and R^2. Reported calibrated performance: $R^2 \approx 0.80$, correlation ≈ 0.91, and low error (RMSE ≈ 1.82, MAE ≈ 1.58). Sensitivity analysis compares imputed vs complete-case datasets.	Sparse meteorological coverage (few stations, some districts lack rain gauges) may bias district estimates, climate and malaria missing values are imputed (potential smoothing/bias).	General population
Ghana. [30]	Statistical/spatial models: Getis-Ord Gi*, Ordinary Least Squares regression, and Geographically Weighted Regression (GWR). Spatial scale: local/cluster-level (DHS clusters displaced up to 2 km urban / 10 km rural) aggregated to administrative districts, national coverage. Climate input data: aridity index, precipitation, rainfall, temperature (mean daytime land surface temperature), and vegetation (EVI).	Performance assessed via model fit and diagnostics: OLS adjusted $R^2 \approx 0.502$; GWR adjusted $R^2 \approx 0.843$ with improved AIC (more negative) relative to OLS.	Possible coefficient bias from localized collinearity in Geographically Weighted Regression. Climate covariates are proximal environmental measures (including LST rather than station air temperature), which may not fully represent exposure relevant to transmission dynamics.	Children aged 2–10 years
Nigeria. [18]	Statistical/spatiotemporal model using GIS, Remote Sensing (RS), and Multi-Criteria Decision Analysis (Analytical Hierarchical Process - AHP). Spatial Scale: Local/District (8 Local Government Areas in Ondo State).	Validation: Internal statistical validation using multiple linear regression (collinearity diagnostics, significance tests). Metrics Used: Beta coefficients, significance (p-values), Variance Inflation Factor (VIF),	Data scarcity, lack of fine-scale temporal resolution, missing intervention/confounder variables, assumption of static land use, limited representativeness of satellite data.	General population of Ondo State.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	Climate inputs: Temperature, rainfall, and relative humidity; environmental inputs included vegetation (NDVI), elevation, slope, and proximity to water bodies.	tolerance levels for multicollinearity. Uncertainty Quantification: Limited; only regression diagnostics provided. Transferability: Limited to Ondo State context; not generalized to other regions.		
South Africa. [24]	Statistical/spatiotemporal time-series modeling using Seasonal Autoregressive Integrated Moving Average (SARIMA) and SARIMA with exogenous variables (SARIMAX). Spatial Scale: Local (Nkomazi Municipality, 3,256 km²). Climate Inputs: Rainfall, temperature (day/night LST), vegetation (EVI/NDVI), and moisture indices (NDWI).	Validation: Cross-validation using training (80%) and testing (20%) data sets. Performance Metrics: Adjusted R^2, RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), AIC (Akaike Information Criterion). Best-fit Model: SARIMA with rainfall, EVI, NDWI, and LSTN (2-month lag). Uncertainty Quantification: Residual diagnostics confirmed independence and white noise residuals (no autocorrelation). Sensitivity Analysis: Lag testing (0–3 months); rainfall had the strongest effect ($r = 0.74$, $p < 0.001$).	Model did not include human mobility, intervention data, or socio-economic confounders. Overestimation in 2017 predictions and underestimation in 2014 due to missing contextual factors. Restricted to one municipality.	General population
South Africa. [31]	Machine learning, Random Forest (RF) regression. Spatial scale: Local/Micro-geographic (396 sub-places within one district). Climate Inputs: Satellite-derived temperature, rainfall, humidity, altitude, NDVI.	Validation Method: Internal validation via out-of-bag error estimation (cross-validation equivalent). Performance Metric: Coefficient of Determination (R^2). Predictive Accuracy: Highest R^2 values observed for March (0.9023), April (0.8901), May (0.8875).	RF cannot predict beyond training data range. Model less effective for extreme (high) malaria counts. Short temporal window limits seasonal generalization. High zero-counts could bias regression performance.	General population
Rwanda. [14]	Hybrid machine learning model, Geographically Weighted Random Forest (GWRF). Comparative Models: Global Random Forest (GRF) and Geographically Weighted Regression (GWR). Spatial Scale: National, disaggregated to local administrative cell level using Gaussian areal	Model Comparison (R^2): GWR: 0.47 and GWRF: 0.79 (best performance). Validation: Internal cross-validation using out-of-bag (OOB) error. Metrics Used: Coefficient of determination (R^2), Root Mean Square Error (RMSE), % Increase in Mean Square Error (%IncMSE). Uncertainty Quantification: Spatial	Coarse remote sensing resolution for rainfall data. Absence of socio-economic or intervention covariates.	Entire Rwandan population.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	Kriging. Climate Inputs: Temperature, rainfall, humidity, and evapotranspiration.	variation of local R^2 mapped; high R^2 values in southwestern, and northeastern parts of Rwanda.		
Benin. [21]	Statistical model, Hierarchical Poisson mixed regression with multi-level random effects. Spatial Scale: Local/Village-level and household-level. Climate Inputs: Rainfall amount, number of rainy days, NDVI (vegetation index).	Validation: Leave-one-out cross-validation for predictive model; internal validation using model likelihood improvement and R^2. Significant Predictors: Proximity to watercourse ($p = 0.003$), Dry soil ($p = 0.002$), High NDVI ($p = 0.05$), Rainfall intensity and frequency ($p < 0.001$), Seasonal variation ($p < 0.001$). Uncertainty: Random effects at three levels (village, site, catch) used to handle overdispersion and unobserved heterogeneity.	Rainfall data missing in early months. Low infection rates made EIR-based modeling unstable. No socio-economic or intervention data incorporated. Model cannot capture extreme outliers due to overdispersion of data.	Children under five.
Africa (multi-country). [32]	Statistical and spatiotemporal correlation and regression modeling. Mann-Kendall trend test and Sen's slope estimator (for climate and malaria trends), Pearson correlation (association analysis), and multiple regression and spatial regression models (to estimate influence of temperature, rainfall, and humidity on malaria incidence). Spatial Scale: Multi-country (continental scale), North, West, Central, East, and Southern Africa. Climate inputs: Rainfall (RF), temperature (Tmax, Tmin, Tmean), and relative humidity (RHmean, RHmin, RHmax).	Model validation: Internal (via cross-variable and temporal sensitivity analysis). Regression model fit metrics: $R^2 = 0.594$; $F = 12.67$ ($p < 0.001$). Best-fit indicators: Rainfall and maximum temperature are the most predictive; Relative Humidity has weak effect ($R^2 = 0.02$). Uncertainty quantification: Reported through regression diagnostics (AIC = − 162.6; BIC = − 157.8) and regional heterogeneity evaluation. The combined model rainfall, temperature and relative humidity improved predictive accuracy to 59% variance explained.	Lag effect not considered, climate factor can have lag effect. The study is based on relatively short period data and regional datasets. Non-climatic factors effects on malaria are not included in the study well, as malaria can not only depend on climate, but non-climatic factors should also be considered.	General population.
South Africa. [33]	Statistical/spatial modeling. Stepwise Logistic Regression (SLR) with presence-pseudo-absence data for malaria (binary 1/0). Spatial scale: Local (district-level), covering 28 rural villages across semi-arid and subtropical zones. Climatic and Environmental Inputs: Vegetation indices (NDVI, SAVI), moisture	Validation: Internal split-sample (60% training, 40% validation) and bootstrap resampling (n = 10,000). Goodness-of-fit test: F-test ($p = 0.081$), indicating no significant difference between observed and predicted data. Metrics used: Classification accuracy (OA), D^2 (analog of R^2),	Relied on secondary malaria data (1998–2006) from national MIS with possible underreporting and passive case detection. No direct temperature/rainfall data integrated, used proxies from Landsat only.	Residents of rural villages in Vhembe District, mostly subsistence farmers and low-income households.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	indices (a1, a2), water indices (MNDWI1, MNDWI2), green index (GI).	AIC, coefficient of variation (CV = 0.11). Uncertainty and Sensitivity Analysis: Tested five buffer distances (0.5, 1, 5, 10, 20 km) to assess model sensitivity to pseudo-absence spacing. 10 km buffer yielded best results (highest D^2 and lowest AIC).		
South Africa. [23]	Statistical and spatiotemporal analysis. Time series (Spearman correlation), Inverse Distance Weighting (IDW) interpolation, Moran's I autocorrelation, and Ordinary Least Squares (OLS) regression. Spatial scale: Local (village-level). Climate Inputs: Daily rainfall, maximum and minimum temperature (1998–2018).	Spearman Correlation: Rainfall = 0.49; Max Temp = 0.39; Min Temp = 0.56 (all $p < 0.01$). Sensitivity Analysis: Conducted for peak malaria seasons (Jan-Mar, Sep-Nov).	Missing socio-economic and intervention data. Limited climate station density, potential interpolation bias. OLS model cannot capture non-linear effects.	General population.
Benin. [34]	Ecological niche modelling using machine-learning Maximum Entropy. Spatial scale: national (Benin) using gridded bioclimatic predictors. Climate input data: precipitation seasonality, precipitation of coldest quarter, precipitation of warmest quarter; vegetation cover.	Internal validation via random split: 80% training and 20% testing. Performance evaluated using ROC-AUC, reported AUC = 0.871.	Uses contemporary bioclimatic surfaces and does not implement explicit future climate variability scenarios.	General population
Multi-country (Africa and Asia). [35]	Statistical classification models (comparative framework): (1) Generalized Linear Models (binomial logistic GLM) with linear and quadratic terms, (2) Classification and Regression Trees. Spatial scale: multi-country, community-level points, with predictors extracted at each community coordinate. Climate input data: mean temperature (previous quarter; quarter before previous quarter) and mean precipitation (same lags), precipitation of wettest quarter, and precipitation of driest quarter.	Internal validation (train/test split): stratified sampling by parasite, continent, country, and survey year with 70% training and 30% testing. Performance metrics reported for both Classification and Regression Trees and GLM: accuracy, precision, recall, F1-score. Model assumption checking for GLMs uses randomized quantile residuals (RQRs); variable selection via forward stepwise regression. Classification and Regression Trees often showed better out-of-sample performance (accuracy/precision/F1)	Climate effects are modelled using historical covariates/bioclimatic summaries and do not include future climate variability scenarios projections.	General populations

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
		than Generalized Linear Models.		
Nigeria. [17]	Statistical/spatial model using Generalized Additive Models (GAMs) with nonlinear smooth functions and spatial random effects. Spatial scale: Nationwide study covering all 37 states of Nigeria. Climate inputs: Precipitation, humidity, maximum temperature, minimum temperature, potential evapotranspiration (PET), wet days, proximity to water bodies, enhanced vegetation index (EVI), cluster altitude.	Internal validation using residual plots, cross-checking with state-level prevalence. Significant nonlinear effects across all covariates. Significant F-values for predictors (all $p < 0.05$), Spatial effect highly significant ($F = 187.9$; $p < 0.0001$). Addressed multicollinearity through factor analysis (three latent components explained 97% variance).	Cross-sectional 2015 survey, unable to infer temporal causality. No inclusion of socioeconomic or intervention-related factors. Spatial bias, some states (e.g. Borno) had no data due to insecurity.	Under-five children.
Global study (especially Sub-Saharan Africa). [36]	Statistical/spatial model using Geographically Weighted Panel Regression (GWPR). Modeling was conducted at a 0.25° spatial resolution using data from 2000 to 2019 and projected under four CMIP6 climate scenarios (SSP1-2.6 to SSP5–8.5). Climatic inputs included mean temperature, temperature variability, and NDVI, with population density and GDP per capita as socioeconomic covariates.	The geographically weighted panel regression (GWPR) model achieved very high internal accuracy ($R^2 = 0.95$) and strong robustness under 10-fold cross-validation (> 94% fit per iteration). Metrics including RMSE, MAE, correlation (r), and slope ($\beta \approx 1$) confirmed model reliability. However, while spatial accuracy was strong, the projections relied on the assumption that only temperature changes across scenarios, introducing structural uncertainty.	Key assumption: All factors except temperature remain constant between scenarios (ignores changes in population, interventions, or economic development). No temporal dynamics: Annual rather than monthly modeling underestimates short-term effects.	General Population.
Benin. [37]	Machine-learning model (Maximum Entropy). Spatial Scale: National (Benin) and projected to multi-country (African extent). Climate Inputs: Bioclimatic variables, precipitation seasonality, precipitation of coldest quarter, and precipitation of warmest quarter. Other Inputs: Temperature, humidity, vegetation cover, derived from WorldClim datasets.	Validation: Internal validation using 80 train and 20 test splits. Performance Metric: Area Under Curve (AUC = 0.871), indicating strong predictive power. Transferability: Model projected from local (Benin) to continental (Africa) scale to assess generalizability.	Downscaling uncertainty, and interpretability issues; lack of temporal validation and limited consideration of intervention/confounding effects.	General population, particularly those in malaria-endemic areas of Benin.
Ghana. [38]	Ordinary Least Squares (OLS) regression and Geographically Weighted Regression (GWR) models (Statistical and spatiotemporal modeling). Spatial scale: National, with local/district-level	Validation and performance metrics: Internal validation through residual spatial autocorrelation tests (Moran's I: $z = 0.817$, $p = 0.414$, random residuals). Model comparison via	Potential biases from displacement of geospatial coordinates for confidentiality. Possible localized collinearity in GWR model.	Children aged 2–10 years across Ghana.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	geospatial clusters (900 clusters across Ghana). Climate and environmental inputs: Temperature (mean annual land surface temperature), Rainfall (annual precipitation), Aridity index, Enhanced Vegetation Index, ITN (insecticide-treated bed net) coverage.	Adjusted R^2 and Akaike Information Criterion (AIC). OLS Adjusted R^2 = 0.502; GWR Adjusted R^2 = 0.843 (showing strong spatial improvement). AIC improved from − 478.4 (OLS) to -661.7 (GWR).		
Benin. [39]	Statistical/spatiotemporal model integrating climatic, environmental, and socio-economic variables. Spatial scale: Local - cluster level (60 villages, CoZo health zone, southern Benin). Climate and environmental inputs: Monthly mean temperature, rainfall, soil type (fine vs. medium-fine), and house altitude.	Validation: Internal validation via Generalized Estimating Equations (GEE) robust variance estimation, bootstrap resampling, and QIC (model fit) comparison of correlation structures (autoregressive best). Metrics used: Incidence rate ratios, 95% Confidence Intervals, p-values, correlation coefficients for lag analysis. Temperature negatively associated with malaria while rainfall positively associated.	Possible underestimation of socio-economic effects due to cluster-level wealth aggregation. Short period (20 months observation) limits interannual variability assessment.	Children under 10 years.

3.1.2 Middle East and North Africa (MENA)

Studies conducted in the Middle East and North Africa (MENA) region were relatively limited, accounting for only 2 (5.1%) of the studies included in this review. Nevertheless, these studies provide valuable insights into malaria transmission dynamics within arid and semi-arid environments, where climatic conditions differ substantially from those observed in many malaria-endemic regions of sub-Saharan Africa. In particular, the studies highlighted the important role of temperature variability, rainfall patterns, and extreme climatic conditions in shaping mosquito ecology and malaria transmission dynamics.

A study conducted in Iran employed artificial neural networks (ANNs) to assess the potential impacts of climate variability on malaria transmission and demonstrated that increased rainfall and optimal temperatures around 28°C were associated with enhanced mosquito breeding and greater malaria transmission potential [26, 40]. These findings suggest that even relatively small climatic shifts may substantially alter transmission dynamics in environmentally marginal settings, where vector populations are highly sensitive to changes in temperature and moisture availability.

Although evidence from the MENA region remains limited, the available studies indicate that climate-sensitive malaria risk modeling can provide important insights for surveillance and preparedness, particularly in areas vulnerable to environmental change and the potential re-emergence or expansion of malaria transmission. The small number of studies identified also highlights a significant regional evidence gap and underscores the need for further research applying spatial and machine-learning approaches to malaria risk assessment across MENA countries.

Table 4
Modelling approaches, predictive performance, accuracy, and population studied for the Selected Studies in MENA.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
Iran. [40]	Machine-learning model, Artificial Neural Networks (ANNs) using a feed-forward multilayer perceptron (MLP) structure. Spatial Scale: Local (district level). Climate Inputs: Temperature (mean, minimum, maximum), Rainfall, Relative humidity and Sunshine duration.	Validation: Internal validation only, data split into training (60%), cross-validation (15%), and testing (25%) sets. Metrics Used: Mean Square Error (MSE), Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Normalized Mean Absolute Error and Correlation coefficient (R). Most influential variables: rainfall, maximum temperature, and mean temperature.	The projections assume no major change in social or environmental conditions. The model assumes no new malaria prevention or control interventions will occur during the study period (2021–2050). Migration from neighboring countries (Afghanistan and Pakistan) is recognized as a continuing confounding factor influencing malaria transmission.	General Population in Khash city.
Iran. [26]	Statistical/Spatiotemporal Model, Multivariate Linear Regression. Spatial Scale: Local/District level-Six villages in Chabahar District. Climatic Inputs: Temperature, Relative humidity, Monthly accumulated precipitation, Vegetation index.	Validation: Internal validation only. Regression statistics: Multiple R = 0.94, R^2 = 0.88, Adjusted R^2 = 0.78. Metrics Used: R^2 (Coefficient of Determination), Adjusted R^2, Standard Error (SE = 111.8). No probabilistic uncertainty or sensitivity analysis reported.	The model was based only on local environmental variables, limiting generalizability to other regions. Only one year of entomological field data was available for model calibration, potentially reducing temporal robustness.	Six rural village communities in Chabahar city.

3.1.3 Asia

Asia accounted for 11 (28.2%) of the studies included in this review, with research primarily conducted in India, China, Indonesia, Pakistan, Bangladesh, and Vietnam. Across these countries, spatial modeling and machine-learning approaches consistently highlighted the important influence of climatic factors on malaria transmission dynamics, while also demonstrating the role of socioeconomic and environmental determinants in shaping malaria risk.

In India, several studies advanced malaria prediction and risk mapping using a variety of modeling techniques. One study developed a hybrid machine-learning framework integrating ANNs, Support Vector Regression (SVR), and Random Forest algorithms to predict malaria outbreaks in western India, achieving exceptionally high predictive performance (R = 0.99) [41]. Similarly, another study combined an SVM with a Firefly Algorithm to forecast malaria transmission in Rajasthan, identifying temperature and rainfall as the most influential climatic predictors [42]. Complementing these predictive approaches, a GIS-based multi-criteria decision analysis (MCDA) classified India into five malaria risk zones and identified approximately 13% of the country as being at very high risk, particularly in Chhattisgarh, Odisha, Jharkhand, and the northeastern states [43]. Another study incorporated socioeconomic indicators and demonstrated that poverty, inadequate housing conditions, and poor sanitation substantially increased vulnerability to malaria transmission [44].

In China, several studies examined the effects of climatic variability and projected future malaria risk under climate variability scenarios. Rising temperatures in Hainan Province were associated with shifts in malaria incidence peaks toward the rainy season [45]. Other studies demonstrated that humidity and rainfall interact synergistically with temperature to accelerate malaria transmission cycles and increase transmission potential [46, 47]. Furthermore, projections under Representative Concentration Pathway (RCP) 8.5, a high-emission climate scenario characterized by

continued increases in greenhouse gas concentrations and global warming, suggested an expansion of environmentally suitable areas for malaria transmission, particularly in southern and coastal provinces [48].

Studies from Southeast Asia further emphasized the importance of environmental and socioeconomic determinants. In Indonesia, elevation and vegetation density emerged as major predictors of malaria vulnerability and spatial risk patterns [49]. In Vietnam, poverty and forest cover were identified as key factors sustaining residual malaria hotspots despite ongoing control efforts [50]. Similar findings from other Asian settings highlighted the complex interactions among climatic variability, land-use characteristics, ecological conditions, and social determinants of health.

Overall, the studies conducted in Asia demonstrated that malaria transmission is shaped by a combination of climatic, environmental, and socioeconomic factors. While temperature, rainfall, and humidity remained the most consistent climatic drivers, several studies highlighted the added value of integrating land-use, ecological, and vulnerability indicators into predictive models. The widespread application of machine-learning algorithms, GIS-based approaches, and climate-change projections further underscores the region’s growing emphasis on advanced modeling techniques for malaria surveillance, risk mapping, and long-term adaptation planning.

Table 5
Modelling approaches, predictive performance, accuracy, and population studied for the Selected Studies in Asia (n = 11)

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
India. [43]	A hybrid machine-learning forecasting model combining Support Vector Machines (SVM) with a Firefly Algorithm (FFA). Spatial scale: District-level (Jodhpur and Bikaner). Climate inputs: Rainfall, temperature and relative humidity, all obtained from Meteorological records.	The Support Vector Machine-Firefly Algorithm (SVM-FFA) hybrid model achieved high predictive accuracy compared to ARMA, ANN and SVM. Validation was performed using monthly malaria incidence data for 1998–2002 (Bikaner) and 1998–2000 (Jodhpur).	Limited spatial generalizability: model trained only on two districts (Jodhpur, Bikaner).	General population
Bangladesh. [45]	Bayesian geostatistical logistic regression model (mechanistic-statistical hybrid approach). Spatial scale: National and subnational (district and thana levels, 1 km² grid resolution). Climate and environmental inputs: Minimum temperature, elevation, precipitation, and vegetation cover (forest vs non-forest); enhanced vegetation index (2005–2006).	Validation practice: 5-fold cross-validation with random data partitioning; internal validation only. Metrics used: Area Under Curve (AUC = 0.78; 95% CI: 0.74–0.82), Mean Error = -0.11%, Mean Absolute Error = 5.06%. Uncertainty quantification: Full posterior distributions and 25%-75% Bayesian credible intervals used for uncertainty mapping. Sensitivity analyses: Compared models with and without spatial and environmental covariates using Deviance Information Criterion (DIC).	Environmental data lag (2005–2006), possible confounding due to interventions and unmeasured socioeconomic factors; spatial clustering assumptions may not fully capture heterogeneity.	Children aged 2–10 years.
Pakistan. [32]	Suitability/Ecological Niche Model using remote sensing and GIS-based weighted overlay analysis (Multi-Criteria Decision Analysis). Model Inputs: Air temperature, Relative humidity, Water bodies, Normalized Difference Vegetation Index.	Validation: Correlation of risk maps with recorded malaria incidence data and population at risk estimates. No external validation. Strong association between model-predicted high-risk areas and observed malaria cases during monsoon months (Oct 2009). Transferability: Limited to Rawalpindi's topographic and climatic conditions. Authors suggest applicability to other regions if local data and satellite imagery are available.	Water bodies and vegetation contributed less to seasonal variability due to their perennial nature. High-resolution imagery recommended for future modeling.	General Population
China. [47]	Statistical and spatiotemporal models. Distributed Lag Nonlinear Model (DLNM) and	Validation: Internal (model sensitivity checks and lag structure testing).	Underreporting bias from surveillance system (possible missing mild or	General population of Suzhou, China.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	Generalized Additive Model (GAM). Spatial scale: Conducted in Suzhou, a prefecture-level city in the northeast of Anhui Province in China. Climatic Inputs: Average, maximum, minimum Temperature, most frequent temperature (MFT), Relative humidity (%) and rainfall (mm).	Metrics: Relative Risk (RR), Interaction Relative Risk (IRR), Relative Excess Risk due to Interaction (RERI), Attributable Proportion (AP). Uncertainty quantification: Conducted via sensitivity analysis and QAIC model comparison. Best-performing model variable: Average temperature gave lowest QAIC value, indicating best fit.	unreported cases). Single-city data limits generalizability. Lacked socioeconomic and environmental covariates (e.g., land cover, vector habitats). Single meteorological station may not capture microclimate variation	
India. [42]	Hybrid Machine-learning model combining Support Vector Machines (SVM) and Firefly Algorithm (FFA). Spatial Scale: District level (two urban and semi-rural districts). Climatic Inputs: Monthly mean temperature, Monthly mean rainfall, Monthly mean relative humidity.	Validation: Internal validation using separate training and testing sets (80% training; 20% testing). Evaluation Metrics: Normalized Mean Squared Error (NMSE), Coefficient of Determination (R^2), Boxplot residual analysis. Model Comparison: SVM–FFA outperformed all others(SVM: $R^2 = 0.50$, NMSE = 0.32, ANN: $R^2 = 0.37–0.70$, NMSE = 0.29–0.34, ARMA: $R^2 = 0.56–0.66$, NMSE = 0.34–0.39). Best Predictors Identified: Temperature and rainfall.	Model performance tested only on short local datasets, requires validation in other regions. Requires further exploration for multi-step forecasting (like seasonal or annual predictions).	Rural and semi-urban populations of Jodhpur and Bikaner.
India. [44]	Hybrid/ensemble approach combining statistical (SARIMA) and machine-learning (RF, SVM, XGB) models. Compared nine models: Random Forest (RF), Support Vector Machine (SVM), XGBoost (XGB), ARIMA, SARIMA, SARIMAX, RF-ARMA, SVM-ARMA, XGB-ARMA. Variables (from ERA5 reanalysis): Max, min, and mean temperature, total rainfall, average relative humidity, atmospheric pressure, and wind speed.	Validation involved cross-validation, bootstrapping, and Diebold-Mariano tests, confirming the XGB-ARMA model as the most accurate and stable. While machine learning models showed high precision and time-series models high accuracy, the hybrid approach balanced both, offering robust, precise short-term malaria forecasts.	The study focused only on Goa, limiting the generalizability of results to other ecological settings with different transmission dynamics. The models also excluded lagged predictors, assuming immediate climate-disease relationships, which may oversimplify vector response dynamics.	General population.
India. [41]	Hybrid Machine Learning Model combining Probabilistic Principal Component Analysis, Particle Swarm Optimization, and Artificial Neural Network (ANN).	Validation: Internal validation (train-test split, 60:40) on observed data for 2009–2012. Performance Metrics: Correlation Coefficient (R),	High computational cost due to hybrid algorithm; relies only on meteorological variables, excludes socioeconomic or	General Population.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	Spatial Scale: Local-district level (three districts of western India). Climate Inputs: Temperature, Rainfall, Relative Humidity (RH).	Root Mean Square Error (RMSE), and Bias. Uncertainty/Sensitivity: Performed feature importance (Regression Tree Ensemble), correlation analysis, and Partial Dependency Plot (PDP) with ICE curves, identified Relative Humidity as the dominant predictor.	intervention factors.	
India. [43]	Statistical-spatiotemporal model. GIS-based spatio-ecological model combining fuzzy logic and multi-criteria decision analysis (MCDA) through Analytical Hierarchical Process (AHP) and Weighted Linear Combination (WLC). Spatial Scale: National (district-level mapping across India). Climate Inputs: Temperature, relative humidity, rainfall. Environmental Inputs: Forest cover, soil type, slope, altitude, and NDVI (vegetation index).	Validation: Multi-source validation using: (i) secondary surveillance data, Annual Parasite Incidence by district (2010–2012), and (ii) primary field microscopy surveys (2012–2016) across 10 states. Sensitivity Analyses: Indicator influence weighted, Soil (25%), Forest (20%), Climate Suitability (15%), Rainfall (15%), NDVI (10%), Slope (10%), Altitude (5%)	Possible underreporting of malaria cases affects validation strength. Does not integrate human behavioral or intervention data.	General Indian population.
Indonesia. [49]	Hybrid GIS-statistical model. GIS based Multi-criteria Decision Model using Analytical Hierarchy Process (AHP). Spatial Scale: District/regional (Purworejo Regency). Climate Variables: Rainfall, humidity. Other Variables: Vegetation density (NDVI), land use/land cover, soil texture, elevation, Settlement density.	Validation: Cross-validation of NDVI with Google Earth imagery (82% accuracy). Land use/cover classification accuracy (31% cloud cover issues). Final vulnerability map validated using malaria case data (2007–2011) from Purworejo Public Health Office. Transferability: Applicable to other tropical rural districts in Indonesia but limited by data temporal mismatch.	Validation data (2007–2011) not temporally aligned with input satellite data (2019–2020). Assumes equal parameter independence in overlay, which may oversimplify interactions.	General Population.
China. [48]	Maximum Entropy (MaxEnt) ecological niche model. Spatial Scale: National (10×10 km grid resolution); future projections for 2030s, 2050s, and 2080s. Climate Inputs: Temperature, rainfall, relative humidity, elevation, Normalized Difference Vegetation Index (NDVI), land cover, and population density.	Validation Practice: 75% training and 25% test split with 10-fold cross-validation. The jackknife test revealed that temperature was the most influential predictor of malaria suitability (accounting for around 45% of model contribution for P. vivax and 40% for P. falciparum), followed by vegetation indices (NDVI), precipitation, and elevation.	Validation limited to environmental suitability not incidence. Did not include socioeconomic or intervention data.	General population.
Viet Nam. [50]	Bayesian zero-inflated Poisson regression (statistical/spatiotemporal	Validation approach: Internal model validation via Bayesian posterior	Data quality issues and underreporting in routine	General population in Viet Nam.

Country	Modelling Approaches Used	Predictive Performance and Accuracy	Limitations	Populations Studied
	model). Spatial scale: district level. Climate inputs: Minimum temperature, median long-term average precipitation, elevation, and forest cover as environmental covariates.	diagnostics (convergence, credible intervals). Metrics used: Posterior means, 95% Bayesian credible intervals.	surveillance data. Temporal limitation, short 2year dataset (2007–2008) may not capture interannual variability. Lack of up-to-date forest cover and dynamic land use data (used 2005 data).	

3.2 Vulnerable Population

Of the 39 studies included in this review, 13 focused explicitly on vulnerable populations across countries such as Ghana, India, Nigeria, Togo, Benin, and Zimbabwe. These studies primarily examined children under five years of age, pregnant women, and rural or low-income communities. Collectively, they demonstrated that malaria risk is disproportionately concentrated among these groups due to a combination of climatic, socioeconomic, and environmental factors, including poverty, inadequate housing, limited access to healthcare services, and heightened exposure to climate-sensitive transmission environments.

Children under five years of age were the most frequently investigated vulnerable population, particularly in sub-Saharan Africa. Studies conducted in Ghana, Nigeria, Togo, and Benin consistently showed that climatic variability, especially changes in rainfall and temperature, increased malaria risk among young children, often interacting with poverty, poor housing conditions, and limited access to insecticide-treated bed nets [16, 17, 19, 21]. Bayesian spatio-temporal analyses in Ghana identified persistent malaria hotspots in the Ashanti and Eastern regions, where children experienced a disproportionately high burden of disease [16]. Similarly, studies from Benin and Togo revealed significant spatial clustering of malaria among children under five in rural districts characterized by inadequate drainage systems, dense vegetation, and favorable mosquito breeding conditions [19, 21].

Pregnant women were less frequently examined but were consistently identified as a high-risk population. A study conducted in Mberengwa District, Zimbabwe, reported that pregnant women, together with children under five years of age, experienced the highest burden of malaria in the country [25]. This increased vulnerability was attributed to limited healthcare access, poor living conditions, and environmental factors that were further exacerbated by climate variability. Rising temperatures and changing rainfall patterns were found to increase the suitability of local environments for malaria transmission, thereby amplifying risks for already vulnerable populations [25].

Rural and low-income communities emerged as the population groups most consistently affected by malaria across the reviewed studies. In Benin and the DRC, malaria incidence increased following rainy seasons in agricultural communities where poor housing quality, inadequate drainage infrastructure, and proximity to mosquito breeding sites facilitated transmission [21]. Similarly, studies from India demonstrated that residents of low-income communities faced elevated malaria risk due to overcrowded housing, inadequate sanitation, and limited access to safe water and healthcare services [44]. These findings indicate that socioeconomic disadvantage and environmental vulnerability frequently coexist, creating conditions that intensify malaria transmission and increase susceptibility to adverse health outcomes.

Overall, the reviewed evidence suggests that climate-related malaria risks are not distributed uniformly across populations. Rather, climatic factors such as rainfall and temperature interact with underlying social, economic, and environmental vulnerabilities to produce disproportionate impacts on children, pregnant women, and disadvantaged rural communities. These findings highlight the importance of incorporating vulnerability indicators into malaria risk models and ensuring that climate adaptation and malaria control strategies prioritize the populations most at risk.

3.3 Modelling Approach

3.3.1 Mathematical and Statistical Models

A total of 23 studies applied mathematical and statistical modeling approaches to investigate the relationship between climatic factors and malaria transmission. Among these, Bayesian hierarchical, geostatistical, and spatio-temporal models were widely used to quantify the effects of climate variables while accounting for spatial dependence, temporal variability, and uncertainty in transmission estimates [15, 16, 51]. Generalized Additive Models (GAMs) and other regression-based frameworks were also frequently employed to examine potentially non-linear associations between rainfall, temperature, vegetation indices, and malaria incidence [17, 18].

Across the reviewed studies, temperature and rainfall consistently emerged as the most influential climatic predictors of malaria transmission, while humidity and vegetation-related indicators generally exhibited secondary but statistically significant effects [23, 24]. These modeling approaches proved particularly valuable for identifying climatic risk factors, quantifying their relative contributions, and generating spatially explicit estimates of malaria risk. Their transparent structure and interpretability also facilitated the communication of findings to policymakers and public health practitioners.

Despite these strengths, mathematical and statistical models exhibited several limitations. Many conventional regression-based approaches rely on assumptions of linearity, independence, and spatial stationarity, which may not adequately reflect the complex and dynamic relationships underlying climate-sensitive malaria transmission [15–18, 23, 24, 51]. Consequently, these models may have limited capacity to capture high-order interactions, threshold effects, and non-linear responses to climatic variability. Nevertheless, they remain important tools for hypothesis testing, risk estimation, and epidemiological inference, particularly when interpretability and explanatory power are prioritized over purely predictive performance.

3.3.2 Machine Learning Models

Ten studies included in this review applied machine-learning (ML) techniques to predict malaria risk and investigate how climatic and environmental factors influence malaria transmission. These approaches are increasingly being adopted because of their ability to process large and complex datasets, model non-linear relationships, and identify interactions among variables that may not be captured by traditional statistical methods [41, 52]. The most commonly applied algorithms included Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and Gradient Boosting methods such as Extreme Gradient Boosting (XGBoost) [22, 41, 52].

Overall, machine-learning models demonstrated strong predictive performance, with many studies reporting accuracies exceeding 90%, particularly when satellite-derived environmental indicators were integrated with meteorological variables such as rainfall, temperature, and humidity [27]. These findings highlight the potential of ML approaches for malaria surveillance, risk mapping, and early-warning systems in climate-sensitive settings.

Several studies illustrated the advantages of machine-learning methods in capturing spatial and environmental complexity. In Rwanda, a Geographically Weighted Random Forest (GWRF) model successfully characterized spatial variations in malaria incidence and demonstrated that the relationship between malaria transmission and environmental factors varied considerably across geographic locations [14]. The model identified rainfall and land surface temperature (LST) as the most influential predictors and revealed elevated malaria risk in the eastern and southern regions of the country [14].

Similarly, in Iran, an Artificial Neural Network (ANN) was used to simulate the potential impacts of future climate change on malaria transmission. The model projected increases in malaria incidence under the high-emission Representative Concentration Pathway (RCP) 8.5 scenario, suggesting that warmer and wetter environmental conditions could create

more favorable breeding habitats for mosquito vectors. Rainfall, mean temperature, and humidity emerged as the most influential climatic determinants of malaria transmission [40].

In India, a study combined multiple machine-learning algorithms, including Random Forest, Support Vector Machines, and XGBoost, to predict malaria vulnerability. Among the evaluated approaches, the integrated machine-learning framework achieved the highest predictive performance, demonstrating strong accuracy in capturing the combined effects of climatic and socioeconomic factors on malaria risk [41]. The analysis identified rainfall, vegetation indices, and population density as major contributors to malaria vulnerability [41].

Beyond climatic variables, machine-learning approaches also highlighted the importance of human-induced environmental changes. A multi-country study conducted across Asia and Africa applied Random Forest and Gradient Boosting models to examine the interaction between environmental and socioeconomic determinants of malaria transmission [52]. The findings revealed that deforestation, irrigation practices, and population growth were significant predictors of malaria distribution, emphasizing that human activities can amplify or modify the effects of climatic factors on malaria risk [52].

Collectively, these studies demonstrate that machine-learning methods offer substantial advantages for malaria prediction by capturing complex, non-linear, and spatially heterogeneous relationships among climatic, environmental, and socioeconomic variables. While their predictive performance often exceeds that of traditional statistical approaches, challenges related to model interpretability, transparency, and generalizability remain important considerations for their application in public health decision-making and malaria control programs.

3.3.3 Hybrid Models

Six studies included in this review applied hybrid modeling approaches that combined traditional mathematical or statistical methods with machine-learning techniques. These approaches are particularly valuable because they leverage the complementary strengths of both modeling paradigms. By integrating interpretable statistical frameworks with the predictive capabilities of machine-learning algorithms, hybrid models can improve both the understanding of climate–malaria relationships and the accuracy of malaria forecasting.

For example, a study conducted in India employed a Support Vector Machine–Firefly Algorithm (SVM-FFA) model to enhance malaria prediction and forecasting performance [42]. The Firefly Algorithm was used to optimize the parameters of the SVM, resulting in improved predictive accuracy compared with conventional statistical approaches. The study identified temperature, rainfall, and relative humidity as the primary climatic drivers of malaria incidence and demonstrated that the hybrid model was better able to capture both seasonal patterns and lagged climatic effects than traditional regression models [42].

Another study developed a hybrid framework integrating Autoregressive Integrated Moving Average (ARIMA), Random Forest, and XGBoost models to analyze temporal trends in malaria transmission [36]. By combining time-series forecasting with machine-learning techniques, the model was able to account for both seasonal fluctuations and complex non-linear relationships between climatic variables and malaria incidence. The hybrid approach outperformed individual models, particularly in detecting seasonal variations and sudden increases in malaria cases associated with changes in temperature and rainfall [36].

In Benin, researchers developed a hybrid early-warning system that integrated Support Vector Machines (SVMs) with real-time meteorological data to predict malaria outbreaks [22]. The system continuously updated forecasts using recent weather observations, enabling the timely identification of high-risk transmission periods. The study reported strong predictive performance, with accuracies exceeding 80%, and highlighted the potential of such systems to support surveillance activities, resource allocation, and public health decision-making [22].

Overall, the reviewed evidence suggests that hybrid models offer important advantages for both understanding and forecasting malaria transmission. By combining the explanatory strengths of statistical models with the predictive power of machine-learning algorithms, these approaches can better capture the complex, dynamic, and non-linear relationships linking climate variability to malaria risk. Consequently, hybrid models represent a promising direction for the development of robust climate-informed malaria early-warning and decision-support systems.

4. Discussion

This review synthesized evidence from 39 studies examining the relationship between climate variability and malaria transmission using a range of mathematical, statistical, machine-learning, and hybrid modeling approaches. Most studies were conducted in Africa (66.7%), reflecting both the region's disproportionate malaria burden and the increasing application of spatial and predictive modeling techniques to support malaria surveillance and control efforts [14, 21, 23]. Across the reviewed studies, temperature and rainfall emerged as the most influential climatic determinants of malaria transmission, while humidity, vegetation, and elevation also played important roles, although their effects varied across ecological and geographic settings [15, 16, 24].

Among the 39 included studies, temperature was identified as a key predictor in 36 studies, rainfall in 30 studies, humidity in 23 studies, and vegetation indicators, most commonly the Normalized Difference Vegetation Index (NDVI), in 20 studies. Elevation and land surface temperature (LST) were examined less frequently, appearing in 9 and 5 studies, respectively. These findings indicate that although temperature and rainfall remain the dominant climatic drivers of malaria transmission, additional environmental factors contribute substantially to local transmission dynamics and should not be overlooked when developing predictive models.

The evolution of modeling approaches observed across the reviewed studies reflects broader advances in data availability and computational capacity. Earlier studies predominantly relied on mathematical and statistical models because of their transparency, interpretability, and ability to quantify associations between climatic variables and malaria outcomes. More recently, researchers have increasingly adopted machine-learning and hybrid approaches capable of processing larger and more complex datasets, identifying non-linear relationships, and improving predictive performance across diverse epidemiological settings [22, 52]. This transition highlights a growing emphasis on prediction and early warning, complementing the explanatory strengths of traditional epidemiological models.

The review also demonstrated that malaria risk is not distributed uniformly across populations. Vulnerable groups, particularly children under five years of age, pregnant women, and low-income rural communities, were consistently identified as bearing the greatest burden of disease. Their heightened vulnerability reflects the interaction between climatic exposure and underlying social determinants, including poverty, poor housing quality, limited access to healthcare services, inadequate sanitation, and close proximity to mosquito breeding habitats [21, 25, 44]. These findings reinforce the importance of integrating vulnerability indicators into malaria risk models and tailoring intervention strategies to populations at greatest risk.

The overall findings of this review are consistent with previous research demonstrating that climate variability are major determinants of vector-borne disease transmission. Similar patterns have been reported for other mosquito-borne diseases, including dengue and Zika, where rising temperatures and altered rainfall patterns have been associated with increased vector abundance and transmission risk [53, 54]. Although malaria shares many climate-sensitive characteristics with these diseases, its transmission is particularly dependent on specific temperature thresholds that influence both mosquito survival and parasite development. Previous research has shown that malaria transmission may decline sharply when temperatures exceed approximately 33°C, whereas dengue transmission can persist under warmer urban conditions [55]. These differences underscore the importance of disease-specific modeling approaches when assessing the health impacts of climate variability.

Despite substantial progress in climate-sensitive malaria modeling, several important knowledge gaps remain. Most studies focused primarily on temperature, rainfall, and humidity, while relatively few incorporated additional environmental variables such as wind speed, soil characteristics, vegetation structure, water bodies, or land-use change [14, 21, 24, 43]. These factors can strongly influence mosquito breeding habitats, vector survival, and transmission dynamics. For example, studies conducted in Benin and Rwanda demonstrated that soil type, vegetation density, and proximity to water bodies significantly influenced malaria distribution [14, 21]. Similarly, research from India incorporated land-use and forest-cover variables into malaria risk mapping, highlighting the importance of ecological determinants in sustaining malaria transmission [43]. Nevertheless, such comprehensive environmental modeling remains relatively uncommon, largely because high-resolution ecological datasets are not consistently available across malaria-endemic settings.

A similar limitation applies to socioeconomic variables. Factors such as migration patterns, housing quality, occupational exposure, education, and healthcare accessibility are rarely incorporated into predictive models despite their well-established influence on malaria risk. This omission is often driven by limitations in data availability, quality, and spatial resolution. Consequently, many studies continue to rely primarily on readily accessible climatic datasets, potentially overlooking important social and environmental drivers of transmission.

Future research should prioritize integrated modeling frameworks that simultaneously incorporate climatic, environmental, and socioeconomic determinants of malaria transmission. Such approaches would provide a more comprehensive representation of the complex systems that govern malaria risk and improve the accuracy and operational relevance of predictive models. Expanding access to open-source climate, environmental, and health datasets would further facilitate model development, validation, and comparison across regions. In addition, machine-learning and hybrid approaches should be increasingly incorporated into national and regional malaria early-warning systems, linking real-time climate information with local surveillance networks. Stronger collaboration among researchers, public health institutions, meteorological agencies, and climate-related organizations will be essential for translating predictive models into actionable tools that support malaria prevention, climate adaptation, and evidence-based public health decision-making.

5. Conclusion

This systematic review synthesized evidence from 39 studies that applied a range of modeling approaches to investigate the relationship between climate variability and malaria transmission. The included studies were categorized into three broad groups: mathematical and statistical models, machine-learning approaches, and hybrid models that combined elements of both. Collectively, these studies provide robust evidence that climatic and environmental factors, particularly temperature, rainfall, humidity, vegetation, and elevation, play a central role in shaping malaria transmission dynamics across diverse geographic settings.

Mathematical and statistical models continue to provide valuable tools for describing disease dynamics, quantifying climate–malaria relationships, and generating interpretable estimates of risk. At the same time, machine-learning approaches have demonstrated substantial potential for improving predictive accuracy, integrating heterogeneous data sources, and capturing complex non-linear relationships between climatic variables and malaria outcomes. Hybrid models, which combine the interpretability of traditional approaches with the predictive capabilities of machine-learning algorithms, are emerging as particularly promising tools for malaria forecasting, surveillance, and early-warning applications.

Despite these advances, several important limitations and research gaps remain. Many existing models focus primarily on a limited set of climatic variables, most commonly temperature, rainfall, and humidity, while giving less attention to broader environmental, socioeconomic, demographic, and behavioral determinants of malaria transmission. Factors such as migration, occupation, housing quality, healthcare accessibility, education, and population mobility are rarely incorporated despite their recognized influence on malaria vulnerability and disease risk. Furthermore, the limited availability of standardized data-sharing frameworks and harmonized datasets reduces model comparability, reproducibility, and external validation across different geographic settings.

Future research should prioritize integrated, multi-dimensional modeling frameworks that combine climatic, environmental, epidemiological, and socioeconomic data to better capture the complex determinants of malaria transmission. Expanding access to high-quality, interoperable datasets and strengthening data-sharing mechanisms would facilitate model validation and improve the generalizability of findings across regions. In addition, greater integration of machine-learning and hybrid approaches into national malaria surveillance systems could enhance early-warning capacity, support targeted interventions, and strengthen preparedness in climate-sensitive settings.

By addressing these gaps, climate-informed malaria modeling can move toward the development of more accurate, scalable, and locally relevant predictive tools. Such advances will not only improve our understanding of malaria dynamics under conditions of increasing climate variability and change but also support evidence-based policymaking, timely public health interventions, and more effective malaria control and elimination strategies worldwide.

Declarations

Ethics approval and consent to participate: Ethical approval was not required for this study as it involved the analysis of secondary, anonymized data and did not involve direct interaction with human participants or access to identifiable personal information.

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

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Figures

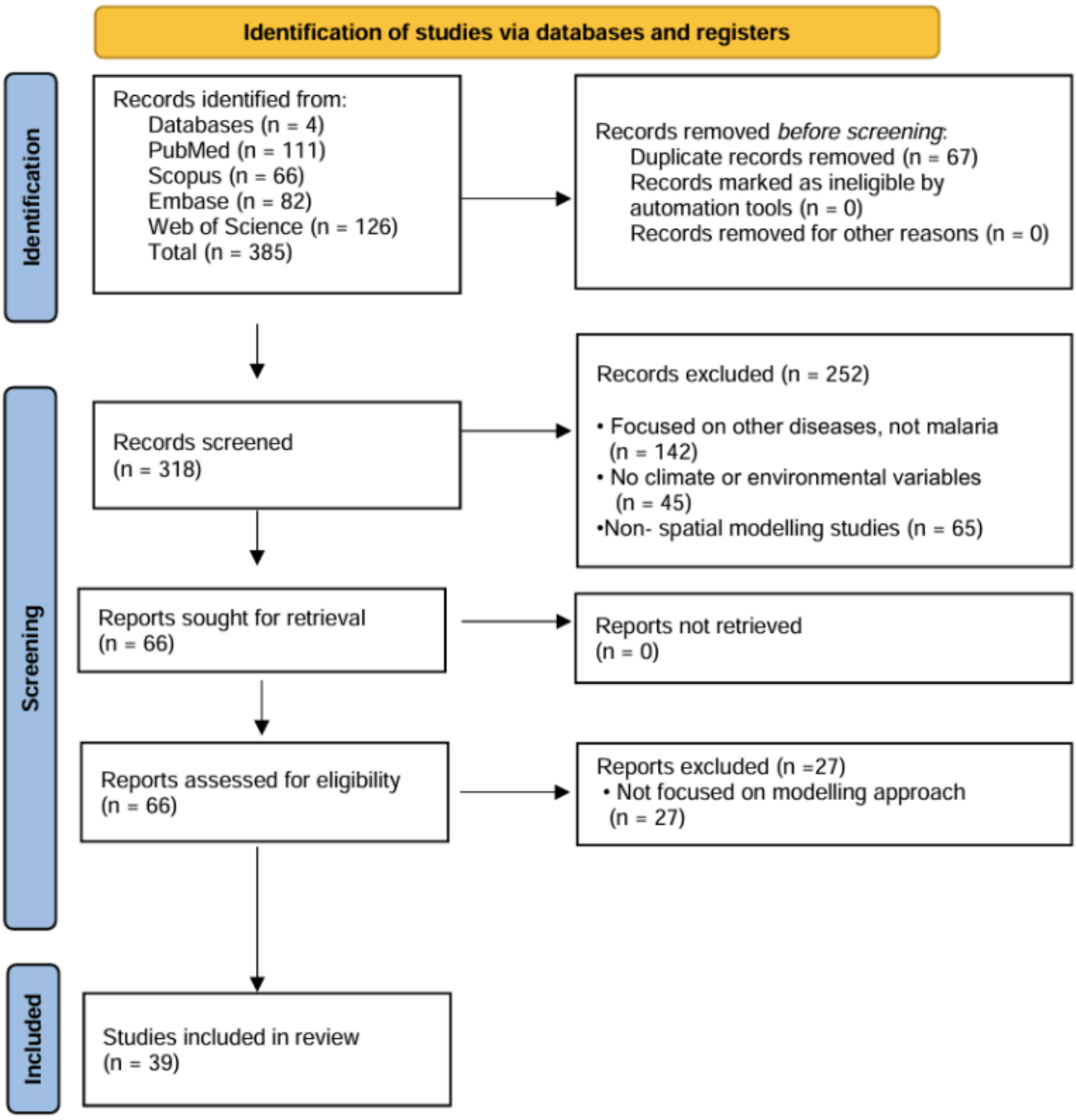


Figure 1

PRISMA flow diagram illustrating the study selection process for the systematic review.

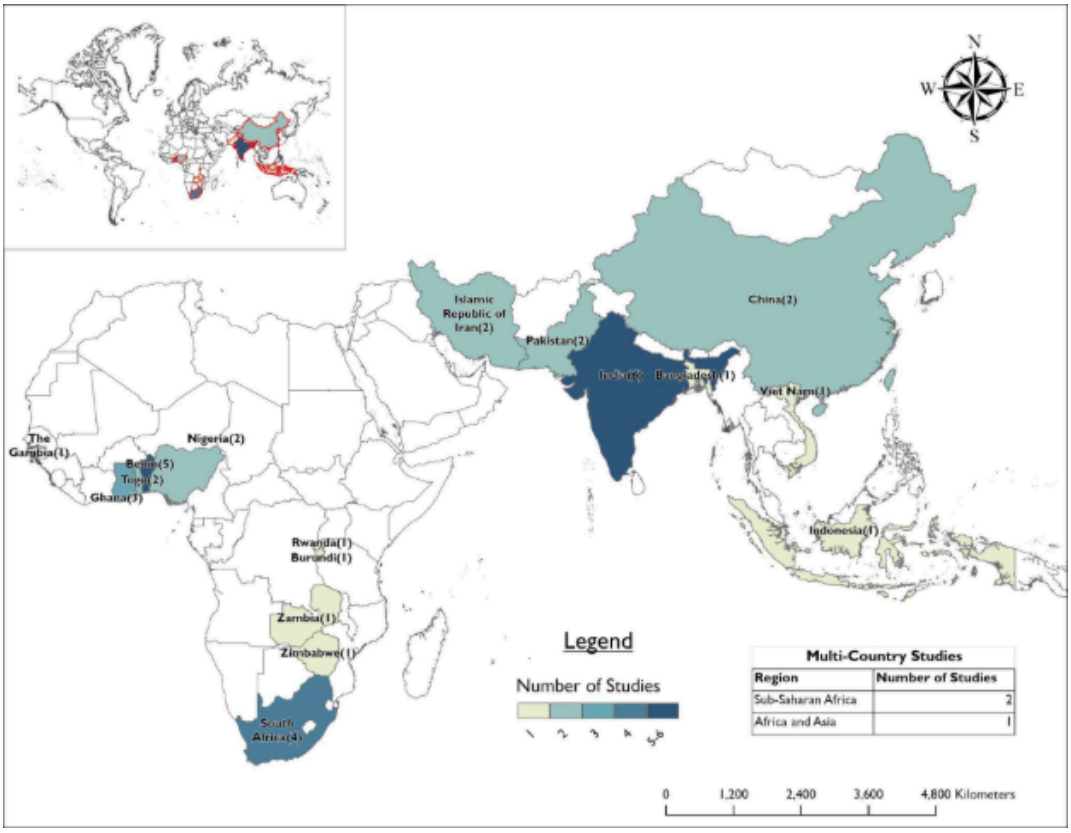


Figure 2

Number of Studies by Geographic Region

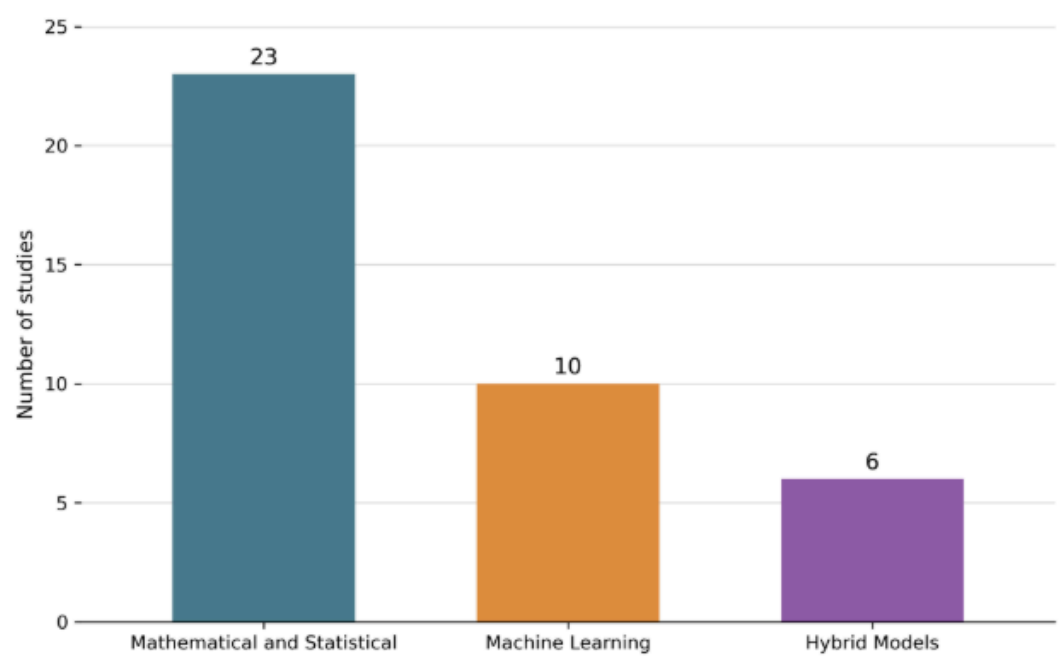


Figure 3

Number of Studies by modelling approach

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