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A systematic review of epidemiological models for malaria transmission in Sub-Saharan Africa

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Abstract

Background Malaria continues to pose a major public health challenge in sub-Saharan Africa (SSA), where more than 95% of global cases and deaths occur. Despite WHO Global Technical Strategy for Malaria (GTS) targeting a 90% reduction in malaria mortality by 2030, progress is hindered by persistent transmission conditions, fragile health systems, and emerging resistance to drugs and insecticides. Epidemiological models are increasingly applied to guide malaria control, yet their diversity and complexity present both opportunities and limitations for policy use. The aim of the proposed systematic review is to explore the epidemiological models that have been applied to malaria transmission in SSA, discuss how these models have been applied in informing malaria control measures as well as long-term elimination planning, and address the methodological strengths, limitations, challenges in implementing them, and their policy and strategic implications.

Methods This study presents a systematic review of malaria modeling efforts in SSA, with a focus on the strengths, weaknesses, and practical applications of different approaches. Following PRISMA 2020 guidelines and a PROSPERO-registered protocol, we searched five databases (PubMed, Scopus, LILACS, Web of Science, and African Medicus Index) for studies published up to December 31, 2024. Eligible articles were screened by three independent reviewers using predefined PECO criteria, and data were extracted on study context, model type, interventions, populations, and outcomes. The quality of the methodology used in the modelling studies that were included was determined using the ISPOR-SMDM good research practices framework. This framework assesses major areas of model structure, assumptions, transparency, validation and reporting. Since most of the included studies represented mechanistic epidemiologic transmission models, rather than clinical prediction, studies, a formal risk-of-bias instrument, like PROBAST, was not utilized. Risk of bias was actually not measured, the modelling quality and reporting practices were instead appraised with the help of the ISPOR-SMDM assessment.

Results Following systematic screening, a total of 102 studies met the inclusion criteria. The most prevalent models were transmission-focused models (52.9%, 54 articles), which involved disease dynamics. Intervention models contributed 21.6% (22 articles), optimal control models 9.8% (10 articles) and combined optimal control-cost-effectiveness

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models 15.7% (16 articles). Key gaps include limited incorporation of drug and insecticide resistance, migration dynamics, and climate variability.

Conclusion We conclude that future modeling for SSA must be better tailored to local transmission patterns, age-specific vulnerabilities, and programmatic needs, while promoting open access, transparent methods, and collaborative use cases. Strengthening the alignment between modeling outputs and policy priorities will be critical for achieving effective and sustainable malaria control in the region.

Keywords Malaria, Sub-Saharan Africa, Epidemiological modeling, Malaria control, PRISMA, Systematic review

Introduction

Malaria is still a major public health concern in this region, since SSA accounts for nearly all cases (95%) due to malaria [1]. With control efforts in place for many years, SSA is still most affected by malaria, as there are good conditions for mosquitoes to breed, the health system is weak, poverty remains widespread and resistance to medications is high. As a result of this problem, the WHO proposed the Global Technical Strategy for Malaria 2016–2030, aiming to reduce both the cases and deaths from malaria by 90% by 2030, based on what happened in 2015 [2]. These goals are largely met by putting strong emphasis on prevention and good case management. Previous studies and guidelines [3–5] recommend ways to prevent malaria are giving out insecticide-treated nets (ITNs), using indoor residual spraying (IRS), Perennial Malaria Chemoprevention (PMC), controlling larvae, performing seasonal malaria chemoprevention (SMC) on children and administering intermittent preventive treatment to pregnant women (IPTp). In addition, successful case management depends on early diagnosis and treatment of malaria, often made easier by community health initiatives that reach under-served areas. Still, even with certain areas reducing malaria rates, progress in SSA is slowed by a range of environmental, population and infrastructure variations.

Over the past decades, epidemiological modelling has contributed to the development of control of the infectious diseases including malaria. Mathematical and computational models give a framework of understanding the dynamics of disease transmission, the investigation of hypothetical situations, and the analysis of possible interventions strategies in cases where the practicality of the application of empirical experiments may be unfeasible, expensive, and unethical. With malaria, models have been applied to predict the patterns of transmission, evaluate the effectiveness of the control effort, predict disease trends, and help in wise allocation of scarce resources [6, 7]. Modelling studies provide evidence-based advice to policymakers, researchers and programme implementers by providing scenario-based projections. Nonetheless, most of the modelling activities directly applied to the national malaria programmes are formulated as part

of collaborative modelling efforts and their presentation in the peer-reviewed literature might not necessarily be as a separate theoretical study.

This systematic review is designed to incorporate both the methodological framework of malaria models and their applications in real world settings. The review begins by categorizing and explaining key modeling approaches used in malaria research. Many researchers rely on deterministic models that give population averages using differential equations to understand major trends and how interventions can affect the spread of a disease [8–12]. Stochastic malaria models can explain malaria transmission under changing conditions, both in places where malaria still exists and in those seeking elimination [10].

The various modeling strategies have distinct benefits in terms of understanding the dynamics of diseases, particularly in a complicated context such as sub-Saharan Africa (SSA). Agent-based models (ABMs) are able to incorporate detailed spatial and behavioral variability by simulating the behaviors and interactions of individual agents such as human beings and mosquitoes and this can be used to capture localized transmission patterns and the interactions between human and vectors. The deterministic models, however, can be applied to single out macroscopic tendencies and protracted results as they streamline processes of the population using the average parameters, which is why they commonly fail to recognize stochasticity and spatial non-homogeneities. The stochastic models contribute a random change in the transmission and development of the disease, which makes the models most useful in observing the imprecision and the low frequented events, especially in low-transmission or emerging epidemic conditions. Although the different types of models have unique advantages to offer, they are also burdened by factors like data requirements, computing resources, and factoring in the realities of the world, such as insect and drug resistance, environmental variability, population migration, and intervention flexibility in the SSA [1].

Malaria is a significant public health concern in SSA with significant economic implications particularly in the resource-limited areas. To control the disease,

appropriate strategies that are aimed at controlling the mosquito vector, the human host or both must be strategized and it is therefore very essential to establish which strategy works best. There are various malaria models that have been developed in SSA and include the simple deterministic to the complex stochastic and agent simulations. Such models vary by complexity, data requirements, and breadth, and they translate differently into many the unique regional transmission patterns and intervention topography. Considering these differences, there has been a great call to governments and policymakers to be advised on the best models that apply depending on the given situations. This review has two objectives: to assess how malaria has been modelled using various protocols in SSA and to determine their relevance, and how models have been utilized, to simulate interventions, measure effectiveness of a programme, and to enable strategic planning. The review offers much-needed knowledge to assist modelers, policymakers, the stakeholders in choosing the most suitable kind of modelling that is suited to their local requirements.

The primary objective of this systematic review, then, is to investigate how epidemiological models have been utilized to investigate malaria transmission in SSA, to evaluate how those models have been utilized to inform malaria control and long-term elimination efforts and to critically evaluate their methodological strengths, limitations, implementation issues and policy implications.

Methods

Study design

A comprehensive systematic search was conducted across five peer-reviewed databases—PubMed, Scopus, LILACS, Web of Science, and the African Medicus Index—from inception to December 31, 2024. The review process adhered to the PRISMA 2020 guidelines [13] for

systematic reviews and meta-analyses (Additional File). The review protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO) under registration number CRD42025639026.

The research question that guided this review was the following: What forms of epidemiological models have been applied to malaria transmission in SSA; how have these models been used to inform malaria control strategies and long-term elimination planning; and what methodological strengths, limitations, implementation challenges and policy implications have been reported?

SSA was termed as a country on the basis of the epidemiological importance of malaria in the African region, such as Sudan and Mauritania.

Search strategy

Five scientific databases method were searched for suitable studies and the detailed list of all search terms is available in (Additional File 2). The search method used MeSH terms and keywords to find results by examining title, abstract and affiliation sections while using corresponding search terms. The results obtained from the search exercise for each MeSH terms and corresponding keywords were merged using 'OR', and the combined results were further combined using a Boolean operator 'AND'. The results obtained from the search were imported into Zotero software for duplicate removal and screening. To facilitate collaborative screening, the titles and abstracts of the 4,503 records retrieved were screened by three independent reviewers (TMA, OMO and KOO) using a shared Zotero group library. This enabled reviewers to have same set of references, tag records and decisions made on documents during screening. Table 1 outlines the inclusion and exclusion criteria that were used to filter out records that were not fit within the predetermined inclusion and exclusion criteria at this

Table 1 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Published before 31st December, 2024	Published later than 31st December, 2024
Focused on studies conducted in SSA	Editorials, commentaries, opinion papers, media reports, letters, bulletins, pre-prints, grey literature
Studies published in the English language	Studies published in languages other than English
Studies modelling malaria transmission with or without intervention components	Not applicable
Was a scientific peer-reviewed publication (Journal and Conference paper (Journal and Conference paper)	Systematic reviews, meta-analyses
Studies applying epidemiological or mathematical models to malaria transmission in SSA	Studies not focused on malaria transmission in SSA
Models that represent malaria transmission dynamics involving human and mosquito populations	Studies not focused on malaria transmission modelling
Mathematical and Epidemiological Models described in peer-reviewed studies	Large-scale modelling platforms or simulation tools not described as standalone studies

stage. Potentially eligible studies were further retrieved and evaluated through full text retrieval. Three reviewers (TMA, OMO and GKA) independently reviewed the retrieved articles in order to establish their qualification to be included in the review. Following the full-text review the reviewers analysed and discussed their reviews to ensure consistency. A third reviewer (AMN) was consulted in the case of an agreement where issues could not be settled through discussion. In the process of screening, the records that were excluded were labeled in Zotero and the causes of exclusion were recorded. In situations where several publications used modeling frameworks that were similar, the individual studies were evaluated independently in terms of their purposes, sources of data, and reported results. The research question in PECO outline (Population, Exposure, Comparator, and Outcomes) is available in (Additional File 3).

Data extraction and analysis

Information extracted from the included study was systematically arranged to enable qualitative synthesis of the findings. Data included (1) the first author and publication year; (2) geographic focus; (3) interventions used in analysis; (4) populations considered; (5) *Plasmodium* species; (6) data sources; (7) conclusion of the article; were extracted from the selected studies into a Microsoft Excel file (Additional file 4.).

Quality evaluation

The quality of the methodology of the included studies was assessed with the help of the guidelines of the ISPOR-SMDM Modeling Good Research Practices Task Force [14]. The evaluation concentrated on major points of model development and reporting such as the clarity of the decision problem and modelling objective, description of health outcomes, transparency in model construct and modelling parameter, reporting of cost inputs where required, connection with prior modelling studies, sensitivity analysis, and model validation. There was also evaluation of additional issues including parameter specification, model transparency (including code availability) and spatial resolution of the models. The results of the detailed assessment are presented in Additional File 5.

Model grouping and evaluation framework

In order to provide a systematic synthesis of malaria research on transmission in SSA, we classified the studies that were included based on the main aim of the research and modelling strategies. All of the eligible modelling studies found in the process of full-text screening were then classified into four broad categories based on the primary focus of analysis.

- Transmission Models, which goals are to simulate malaria's transmission between humans and vectors, often by using either deterministic compartmental models or agent-based approaches;
- Intervention Models, which assess the impacts of one or more interventions such as insecticide-treated nets (ITNs), indoor residual spraying (IRS), seasonal malaria chemoprevention (SMC), and treatment with artemisinin-based combination therapy (ACT);
- Optimal Control Models involve mathematical optimization methods used in determining the most effective intervention strategies to determine the optimal allocation, timing, and intensity of the control measures used in various transmission settings;
- Cost-Effectiveness Models, which compare both the health and economic effects of different malaria control strategies for making resource decisions.

Within each model category, we identified and compared the essential characteristics of all the included models. The evaluation criteria comprised:

- Model Structure and Assumptions—including incorporation of demographic heterogeneity (such as age, sex), ecological factors (such as seasonality, climate), immunity dynamics, and reinfection;
- Intervention or Transmission Mechanisms Addressed—such as coverage levels, resistance dynamics, or treatment strategies;
- Strengths and Limitation—examined in terms of analytical complexity, empirical validation, generalizability, and computational efficiency;
- Comparative Advantages—identifying what differentiates each model from others within or across categories;
- Contextual Use Cases—suggesting areas where the model type is particularly applicable, such as high transmission zones, drug-resistant regions, or mobile populations.

Results

Study selection

A total of 5527 articles were identified from the search. 1,024 duplicates were removed which led to 4,503 articles were screened by title and abstract with 280 articles selected for full-text evaluation. For final analysis, 98 articles [6, 8–12, 15–105] and 4 conference papers [106–109] were included in the final analysis (Fig. 1). The number of full-text articles that were rejected after careful screening was 147. This comprised of studies that were not conducted in Sub-Saharan Africa (n=13), review articles (n=17), not related to malaria (n=39), not a malaria

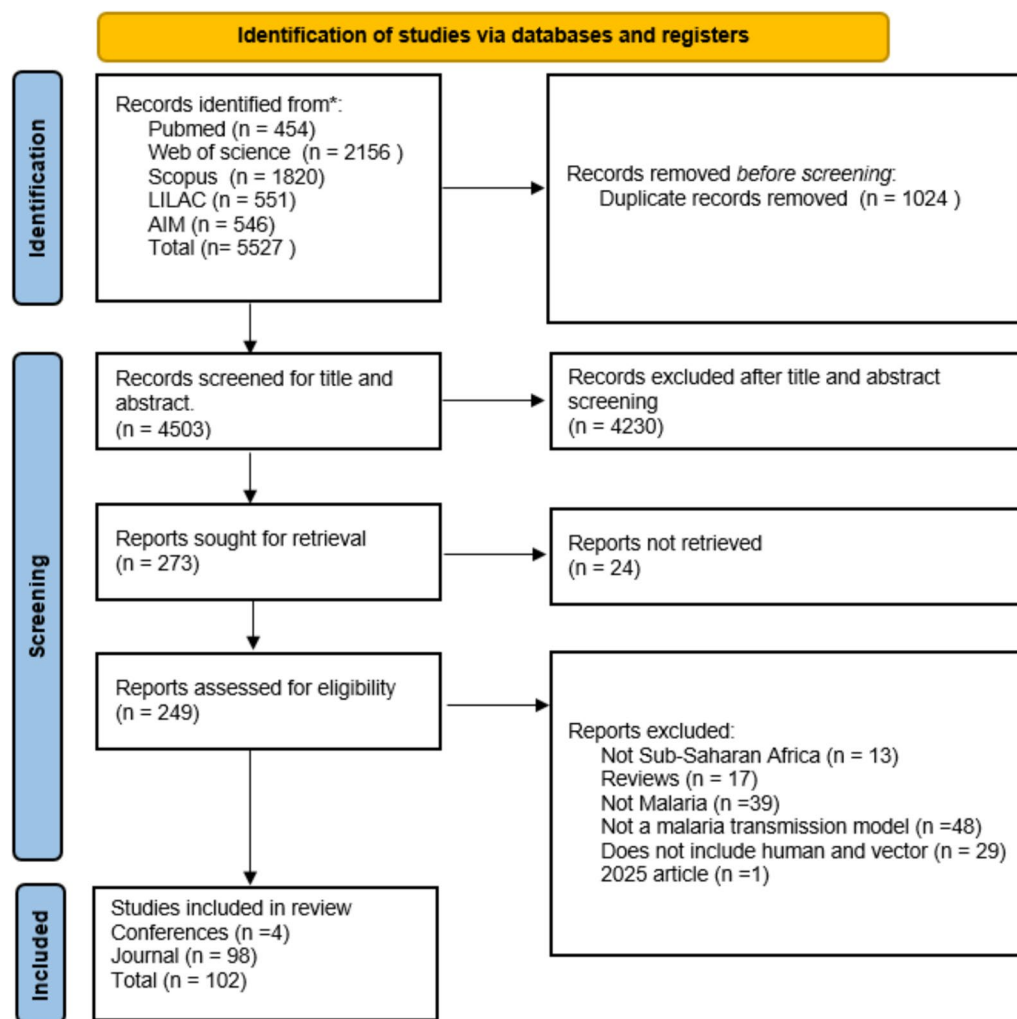


Fig. 1 Summary of systematic screening of identified articles

transmission model (n=48) and did not model both human and vector components of malaria transmission (n=29). Further, one study published in 2025 (n=1) was not included because it fell outside the predefined study period (see Additional File 8 for more details).

Classification of modeling studies

This analysis divided its 102 assessed articles into four main research areas depending on their content focus. The study found transmission-focused models to be the dominant subgroup at 52.9% (54 articles) because they focused on disease transmission patterns and spread dynamics. The examination of different control measures through intervention modeling appeared in 21.6% (22 articles) of the research. 9.8% (10 articles) of the studies used optimal control models to develop infection reduction approaches alongside resource optimization methods. The combination of Optimal Control with

Cost-Effectiveness evaluations formed approximately 15.7% (16 articles) of the reviewed research. Tables 2, 3, 4 and 5 give an overview (pros, cons, advantages over other models and best use case) of all models considered in this review and more details can be found in Additional File 6.

Figure 2 presents the distribution of malaria interventions that were included in the modelling studies included. Over half of the research (54 out of 102; 52.9%) did not specifically present intervention strategies, instead presenting models of malaria transmission dynamics. Among the studies that included interventions, the most commonly modelled control measures included insecticide-treated nets (ITNs)/LLINs (27.5%), treatment of infected people (22.5%), and indoor residual spraying (IRS) (21.6%). Other interventions, vaccination (8.8%), antimalarial drugs (7.8%), and awareness campaigns (5.9%), were underrepresented, whereas a variety

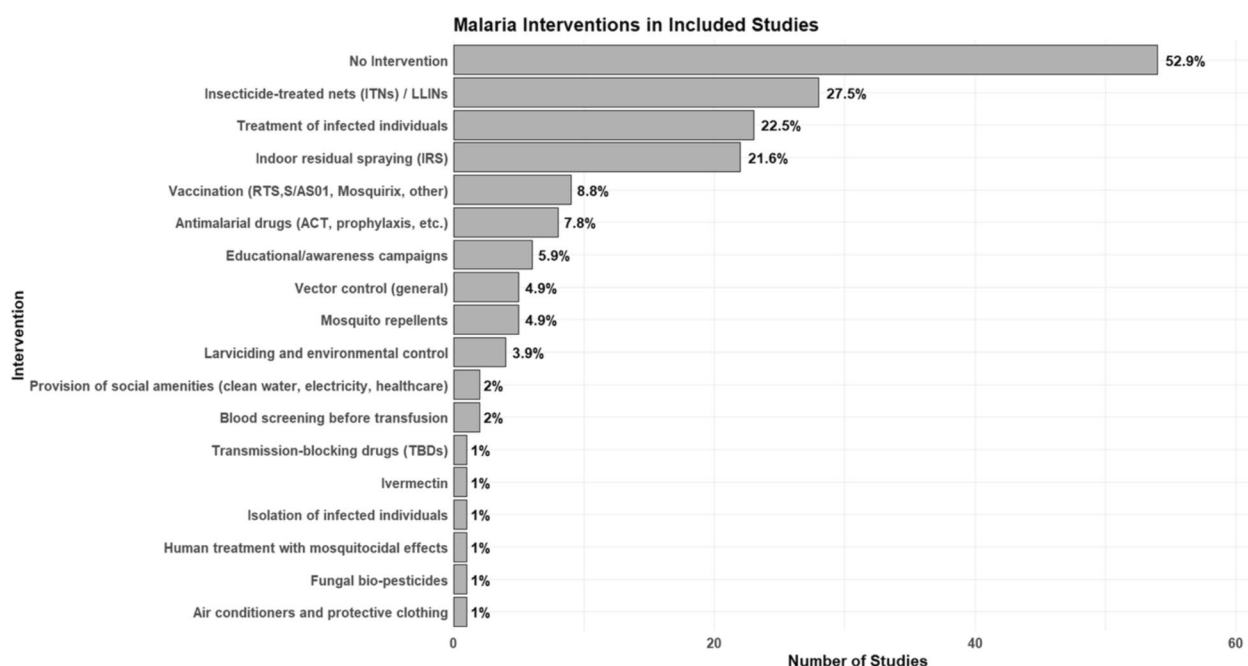


Fig. 2 Distribution of malaria control interventions reported in the included studies

of interventions such as ivermectin, transmission-blocking drugs, fungal biopesticides, and protective measures were mentioned in a very small number of studies (2.1% or less).

A total of 45 articles focused on single-country reports among the 102 included publications, although multiple studies examined more than one country. Nigeria stands as the most researched country in the studies with 19.6% while South Africa follows as the second most studied nation with 15.2%. The analysis includes data from Burkina Faso, Kenya, Tanzania and Malawi were each represented in three to four articles. Single-country evaluations were reported only for Rwanda, Djibouti and Zimbabwe (see Fig. 3). Figure 4 demonstrates that the quantity of malaria transmission modelling studies has been growing over the years, although there was a significant increase starting in 2018. The most publications were in 2020 (15 studies, 14.7%), 2023 and 2024 (13 studies each, 12.7%).

The results of this systematic review are presented through a detailed examination of the identified models, organized by the original study authors (see Tables in Additional file 7). For each model, the review highlights key strengths and limitations, providing a balanced perspective on their design and application. Comparative advantages over alternative modeling approaches are discussed, with particular attention to how each model performs in relation to specific epidemiological or intervention contexts. Additionally, the review identifies the

most appropriate use cases for each model, offering practical guidance for policymakers and researchers aiming to apply these tools in diverse malaria transmission settings across SSA.

Types of modelling approaches for malaria control

Mathematical modelling is becoming an important tool in infectious disease studies to provide robust frameworks to study the dynamics of diseases, gauge intervention effectiveness, and support evidence-based policy in an uncertain setting. Models can enable a researcher to investigate hypothetical scenarios and optimise resource allocation in settings where large-scale empirical experimentation might be unfeasible, expensive or unethical. However, the modelling methods are fundamentally premised on simplifying assumptions, estimations of parameters and the quality of the data available to them; therefore, the results of the modelling methods should be viewed as conditional forecasts as opposed to predictions of actual outcomes in the real world.

In the review, modelling strategies were reviewed in 102 studies related to malaria control strategies and long-term elimination planning in SSA. The articles were classified into four themes: transmission-focused models, intervention-oriented models, optimal control models, and cost-effectiveness models. Each group is presented through a discussion of the benefits of the implemented methods, their practical value, and their role in the research and policy making.

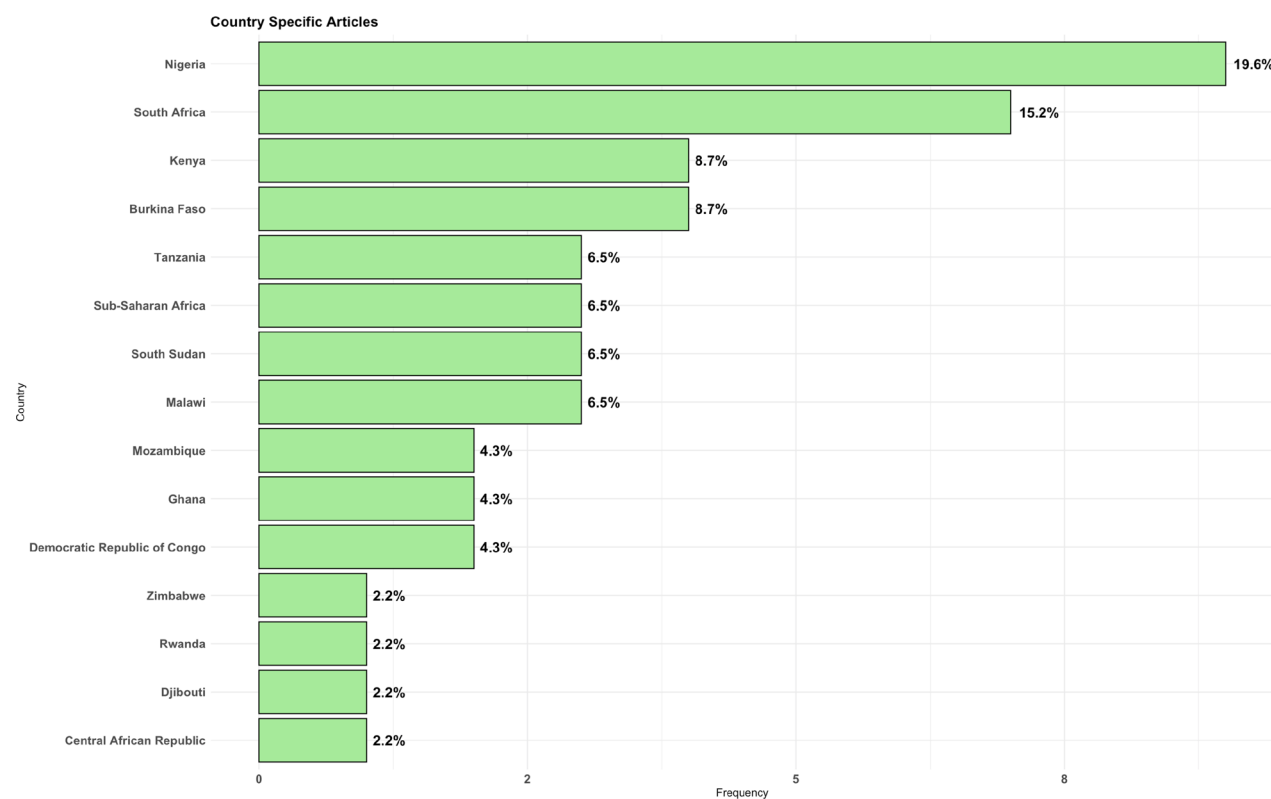


Fig. 3 Country specific articles

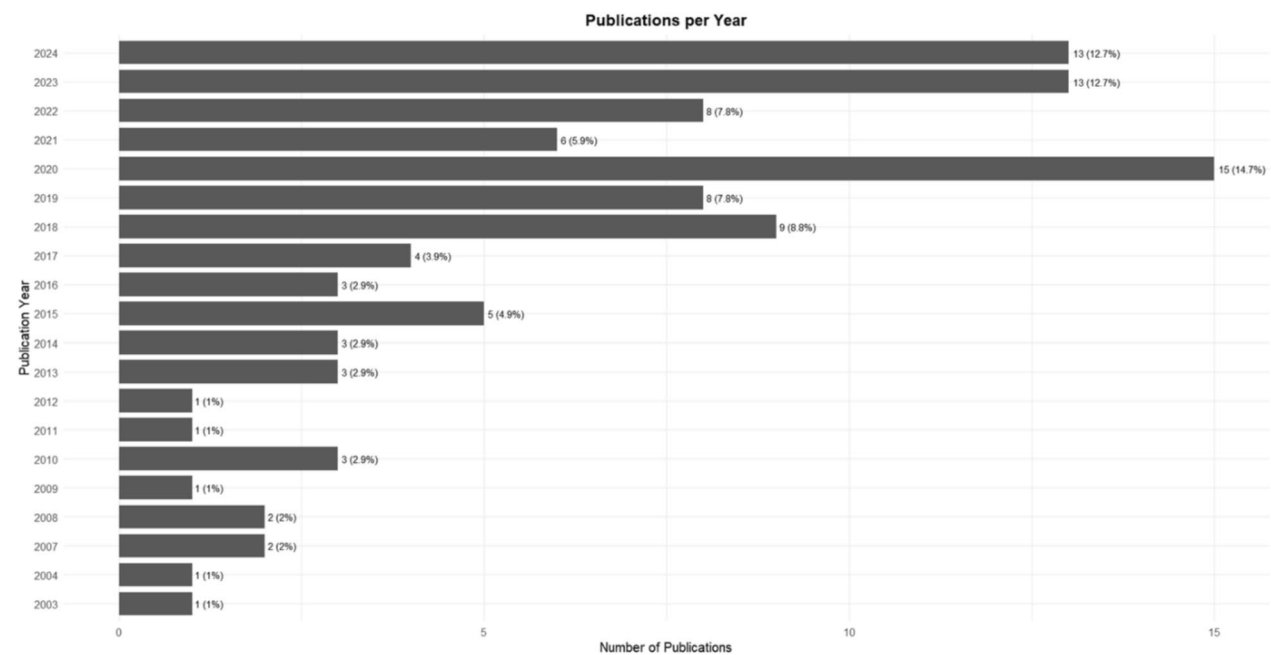


Fig. 4 Distribution of malaria transmission models by year of publication

Transmission-focused models

Transmission-focused models were the main analytical tool used in the reviewed articles and mostly examined the natural pattern of malaria spread in SSA by studying vectors, seasons and the development of immunity. Ecological accuracy is added to these models using temperature and rainfall which matter a lot for mosquitoes' development, overall survival and the timing of their seasons. According to [66, 76, 77], using climate-sensitive methods can better predict the spread of diseases and help develop early warning systems. Besides environmental parts, some models also incorporated immunity, which may lead to temporary protection, cycling infections and less response over time which matter most in areas with continuous outbreaks. According to models by [62, 73, 74, 89], changes in immunity can explain why infectious diseases still persist and fluctuate over time. In some studies, fractional and fractal-fractional calculus were used to introduce memory effects into the models, meaning that the current spread of malaria depends not only on present conditions but also on past infection history. This approach allows the model to better capture prolonged infectious periods and delayed responses within populations. Mittag-Leffler functions were used to mathematically describe these extended infection processes (see [32, 34]). These modeling tools have helped create models for processes with long-term histories and delayed responses. This field continues to attract attention, with the use of complex models for mosquitoes examining their presence, attraction to humans and willingness to bite [24, 40]. This type of information increases our understanding of how mosquitoes develop and react to various types of control strategies. Also, the development of drug-resistant strains has been represented directly in models, providing information on treatment failure and the strength of infectious disease spread in the presence of certain drugs [19, 75].

Intervention-focused models

Malaria control methods like insecticide-treated nets, indoor residual spraying and public health education are evaluated effectively using intervention modeling. Due to the heterogeneity of malaria transmission environments in SSA, intervention models come in handy to adjust the control measures to the local conditions. Human movement, such as the cross-border and migration can cause spatial heterogeneity in transmission and might cause reintroduction of infections in low-transmission regions. Recent research [90, 107] has thus integrated mobility patterns to have a better measure of their effects on intervention effectiveness. Additionally, climate-sensitive models show that fluctuation in the environment (e.g. temperature change and change in rain patterns and so

on) can potentially increase or decrease the abundance of vectors and increase or decrease the intensity of transmission, making long-term efficacy of sustained prevention interventions more challenging.

Interestingly, none of the reviewed intervention-oriented studies explicitly modelled Mass Drug Administration (MDA), even though it is becoming more relevant in the high-transmission and elimination environment. Moreover, although a number of studies considered a combination of measures with regard to vector control and treatment, none of them formally embraced an Integrated Vector and Parasite Management (IVPM) approach. This brings out a significant gap in the coordinated modelling strategies of parasites and vectors.

Optimal control models

Optimal control models are used to apply control theory to the selection of optimal intervention strategies that reduce disease burden and optimize resource utilisation. Models based on Pontryagin's Maximum Principle direct how regulations are used for preventing or controlling the disease. Significantly, [103] examined complications that can arise in blood transfusion in places where malaria is common, while [71, 101] simulated vaccination options for immigrant groups and for children. Such approaches are very useful for planning smart use of resources. More detailed models are able to address matters such as how much counterfeit medicine appears [23] and how pathogen resistance forms [106] which are particularly important in epidemic-prone areas. But many models are developed for narrow use, ignoring cases of reinfection and differences in geographic spread. Notably, none of the optimal control studies explicitly optimized any population-wide drug administration strategies including MDA or assessed formal IVPM models.

Cost-effectiveness models

Many malaria models join epidemiology and economics to assess the economic and human outcomes of different control measures, providing useful policies to help in resource-limited areas of SSA. Evidence suggests that screening for drug resistance helps keep treatment efficient, yet most models do not take into account the different behaviors and immune responses of patients [64]. Study [61] pointed out that limited healthcare and infrastructure lead to different vulnerabilities in dealing with malaria which complicates how to fight it. Although some models [46, 71] specified what herd immunity means regarding administration rates, these also stress that it depends on other control efforts and continued use of vaccines. Work such as [8] showed that paying attention to seasons can help guide effective intervention timing. Recent modelling studies [12, 27] have

incorporated multiple types of interventions at the same time—sometimes using unpredictable elements to better capture real-world changes in disease transmission. Likewise, all the cost-effectiveness studies did not explicitly evaluate MDA programmes or formally incorporate vector-parasite management packages.

Strengths, limitations, and applications

Diverse capabilities of epidemiological models in the dynamics of malaria transmission and intervention strategies have been highlighted in the reviewed articles in understanding the dynamics of malaria transmission and intervention strategies across malaria-endemic areas in SSA. A number of strengths, limitations, and practical uses of these models were found across the literature.

Strengths of existing models

Many models offer a comprehensive description of the malaria transmission processes using climatic, biological, and epidemiological determinants. A number of modelling frameworks combine environmental factors like temperature, rainfall, and seasonality which can enable researchers to identify ecological drivers of malaria transmission more effectively. Other models include the age structure, immunity dynamics, and sensitivity analysis in order to reveal critical parameters that influence the spread of the disease. These characteristics allow understanding more thoroughly the interactions of mosquito vectors, human hosts, and the environment.

Moreover, some of the studies use advanced mathematical and computational methodologies to enhance malaria dynamics. These include stochastic modelling, agent-based simulations and fractional-order models, which incorporate nonlinear dynamics and system memory. Such methods enable the researcher to investigate uncertainty, persistence of infection and possible limits of the disease control.

Limitations of current models

Despite the valuable insights that this systematic review provides regarding the malaria modelling in SSA, there are various limitations worth noting. First, the review did not include narrative reviews, grey literature, preprints, and models that were only reported in National Malaria Control Programme (NMCP) documents. As a result, this may not have reflected some modelling methods that are directly applied to operational planning and policy support. Moreover, numerous studies depended on datasets that are usually constrained in malaria-endemic contexts, such as those needed by climate-sensitive models or models that use human behavioural responses to interventions.

Nonetheless, the models incorporated in this review offer some interesting information to malaria studies and policy discourse notwithstanding these limitations. Numerous studies were created to investigate the dynamics of malaria transmission, analyze environmental and demographic factors of malaria trends, and evaluate possible intervention conditions. Although these studies were not explicitly modelled, they assist in determining critical factors affecting malaria persistence and transmission, which can be added to the existing evidence base employed in strategic planning.

Modelling findings are mostly applicable in any environment based on how the models have been localized using local data. The main model structure is in most instances flexible and the input parameters are tailored to capture variations in transmission intensity, environmental factors, population structure and intervention coverage. Consequently, the modelling transferability is often set by the local data availability and quality and not necessarily by constraints of the modelling framework itself.

The other restriction is associated with the assumptions regarding intervention coverage. There were numerous studies that made the assumption of high or even perfect uptake of interventions like insecticide-treated nets, indoor residual spraying, vaccination or treatment adherence. In practice, intervention coverage and utilization tends to be incomplete and heterogeneous in most SSA settings. This can substantially affect estimates of malaria control impact.

Lastly, few models covered in this review directly incorporated drug resistance or mechanism that allow to simulation of reinfection. These aspects have a significant role to play in malaria transmission in endemic areas yet have been underrepresented in most modelling frameworks. However, there are number of modelling studies that are beyond the focus of this review that have looked at the dynamics of resistance in more detail such as studies [110, 111]. Even though these studies were not part of the systematic analysis due to not fitting the predetermined inclusion criteria, this points to the increasing relevance of the inclusion of the resistance processes in malaria transmission-focused models and gives valuable context to the future modelling work.

Application and use case

This review demonstrates the various applications of epidemiological models in the malaria research and decision-making of malaria in SSA. In the studies reviewed, the dynamics of malaria transmission were often studied with the help of modelling and the impact of interventions, as well as the consideration of various situations that could be applied to malaria control. There were numerous models that were used to investigate the

impacts of vector control strategies, treatment methods, and integration of interventions under different epidemiological circumstances.

Along with the assessment of interventions, there were various modelling methods that explored the broader issues, such as variability of environmental factors, demographic aspects, behavioural alterations of vectors and variation of intensity of transmission with time. These applications facilitate a better insight into disease dynamics and assist in determining the circumstances where the control measures can be the most efficient.

Although not every study that was reviewed specifically assessed intervention strategies, these models still contribute to the discussion of malaria research and policy. Most of the models facilitate the identification of major malaria persistence drivers and point out features like climate variability, population structure, and transmission heterogeneity as some factors that ultimately affect malaria dynamics. Those insights can be useful in the strategic planning process because they can assist policy-makers in being more aware of the possible risk factors, the threshold of transmission, and in what circumstances interventions can be most effective.

Moreover, despite the fact that most of the studies did not publish their model code, conceptual frameworks, modelling assumptions, and analytical findings presented in the literature are valuable in informing future modelling research and in facilitating collaboration between researchers and malaria control programmes. Practically, the creation or functioning of sophisticated models would hardly be expected of national malaria programmes. Rather, modelling activities are usually done in collaboration with scholarly and research institutions. In this regard, even theoretical modelling studies will be part of the overall evidence base that underpins malaria control planning and discussions of the policy.

Altogether, the analyzed articles indicate that epidemiological modelling offers a versatile approach to studying malaria dynamics and assessing possible intervention scenerios and enhancing the evidence base of malaria control measures in the endemic environment.

Cross-cutting themes and practical implications

The observed studies show several common themes. Drug resistance and re-infection remain significant threats to the elimination and control of malaria and, therefore, there is a need to constantly improve and revise the modelling techniques. Climate and environmental variables are also relevant, particularly when it comes to transmission and intervention modelling, as this necessitates fine-scale data in order to provide a more accurate picture. In addition, population heterogeneity including variations in age, immunity and mobility must be clearly

taken into consideration especially when coming up with subnational responses that take into consideration different population dynamics.

One of the most essential cross-cutting weaknesses of all four types of models is that the calibration and validation of the model heavily depend on regular surveillance and data on malaria cases documented through routine surveillance and WHO reporting mechanism. Most SSA health systems experience incomplete coverage of routine health services, especially in the private sector, and mainly includes symptomatic infections that are established by RDT or microscopy. The asymptomatic and submicroscopic infections prevalent in high-transmission zones are usually not detected and thus not classified as official data. Such under-estimation could result in systemic underestimation of the intensity of transmission and biased estimates of intervention effect. Successful malaria management in high-endemic environments needs integrated vector and parasite management strategies that consider the existence of parasite reservoirs [112]. The lack of these epidemiological realities within the models will restrict the impacts of the policy relevance and external validity of the models.

There is a strong emphasis on the importance of integrated control as it is the most effective approach to combine multifaceted interventions to fit local environmental and social context. It is notable that no intervention-based, optimal control, or cost-effectiveness literature reviewed directly included strategies of drug administration on a population-wide scale like Mass Drug Administration (MDA) despite its growing importance in the high-transmission and elimination contexts. In addition, although some studies assessed a combination of the measures of vector control and treatment, none formally implemented a structured Integrated Vector and Parasite Management (IVPM) model. Future modelling studies therefore need to place greater emphasis on the explicit incorporation of MDA plans and co-ordinated parasite-vector control models to influence more realistic malaria control and elimination paradigms. The combination of these strategies in the models of transmission, optimal control, and economic assessment would increase relevance of the policy and would contribute to more comprehensive planning of interventions.

Despite the fact that the current models are valuable contributions to malaria control in SSA, they should be more realistic, have elements of uncertainty, and be in line with the realities of practical policy limitations. Future studies need to start on the creation and development of operational relevant, flexible and adaptive modelling frameworks that can be recalibrated on national epidemiological data and intervention situations to support national malaria control programmes and meet the

WHO global malaria targets. Large-scale individual-based and transmission models are examples of adaptable modelling platforms, in which parameter adjustment to local conditions is possible without affecting the overall structural framework (For instance see, [113, 114]). Examples of such approaches demonstrate that modelling can be adapted to the national requirements of decision-making, as well as that it can be methodologically sound.

Comparative advantages of different modelling approaches

The reviewed modelling studies can prove useful to inform the planning of malaria control and long-term elimination in SSA because transmission, intervention, optimal control, and cost-effectiveness models have different but complementary roles. These modelling paradigms deal with various levels of the decision-making process instead of competing approaches.

Malaria dynamics are based on transmission-focused models which form the epidemiological basis of the dynamics. These models elucidate the structural factors in maintaining the transmission by formalising the interactions between the host and the vectors, immunity formation, climate responsiveness, and the development of resistance. Their comparative advantage is that they are able to determine threshold conditions, which include reproduction numbers and equilibrium states, that cause malaria to continue or to decrease. They are especially useful in theoretical contexts and addressing the manner in which the environment or biological forces influence the patterns of transmission. But in the absence of circumscribed intervention cases, their immediate relevance to operational questions of policy can be restricted.

Intervention models take transmission frameworks further and include particular control interventions, such as ITNs, IRS, chemoprevention, treatment strategies, and vaccination. The most important of their advantages is policy relevance: they measure the expected effect of an intervention or a combination of interventions at different coverage levels. The models are particularly effective in national malaria control programmes that are interested in a comparison of alternative strategies. However, they tend to make their projections based on assumptions about sustained coverage, compliance and behavioural reactions that might not be entirely representative of the actual implementation situations.

Optimal control models also presents a prescriptive aspect whereby mathematical optimisation is used to identify the most efficient use of finite resources with time. The advantage they have over each other is that they help make prioritisation decisions-when and to what extent interventions should be implemented, to

maximize health benefits or minimize losses under resource constraints. Such frameworks are able to facilitate the strategic planning in resource-constrained SSA settings. Nevertheless, the best solutions based on theoretical frameworks might demand scrupulous contextualisation of theoretical ideas into practice due to the limitation on operational, logistical and behavioural levels.

The cost-effectiveness models combine the epidemiological outcomes with the economic analysis. The main strength they have is that they are able to assess value of money and financial sustainability. These models inform the choices made by donors, government and integrated intervention planning by comparing health gains against cost. This economic view is crucial in high burden and resource-constrained settings. Nevertheless, the conclusions will be based on the data and assumptions available on health system capacity and reliability.

On the one hand, these modelling methods can be regarded as different, but complementary, ways of analysis in malaria epidemiology. The characteristics of transmission-focused models shed light on the biological and ecological determinants of malaria persistence as they can offer a background of understanding of the host-vector relationships and environmental forces. Intervention models can be used to translate these dynamics into an applied scenario by estimating the effect of individual control strategies with different assumptions of coverage and effectiveness. Optimal control models build upon this model by determining the optimal strategies to maximise the epidemiological effect or minimise cost within resource constraints to help in strategic allocation decisions. Cost-effective models also incorporate economic aspects and consider the feasibility and worth of alternative intervention portfolios. Notably, there is no single modelling framework that can be used to encompass all biological complexity and operational viability and economic limits of the malaria control. An integrative use of these methods provides a stronger and context-specific platform on sustainability of malaria control initiatives and in the planning of long-term malaria eradication in SSA.

Contextual application of the models

Malaria modelling methods can be applied across SSA depending on the intensity of transmission, availability of data, capacity of a health system, and the policy question to be considered. Studies analyzed suggest that different modelling frameworks are more suitability concerning various epidemiological and programmatic contexts.

Transmission-focused models are most informative when the main aim is to understand the drivers of malaria persistence. In the case of high-transmission

environments, these models help explain how host-vector relationships, immunity and climate variability, and resistance play a role in sustained transmission. They can be especially helpful in determining structural determinants of endemicity and estimating epidemiological thresholds that can be help in determining control feasibility. Their practical use in planning programmes, however, may not be wide unless the elements of interventions are included specifically.

Operational decision-making is more closely aligned with intervention models. These models measure the estimated effects of scaling up individual or combined interventions, e.g., insecticide-treated nets, indoor residual spraying, chemoprevention, treatment approaches, and vaccination. They are particularly applicable to national malaria control programmes measuring coverage goals, intervention mix or subnational differentiation of approaches. Their applicability to policy, nevertheless, is based on realistic assumptions about policy implementation, compliance, and long-term provision.

Optimal control models are best applied in settings where there are constraints in resources that require prioritisation. The models guide strategic allocation decisions by establishing the timing and intensity of interventions that produce the most significant effect on limited budgets. They apply especially well to medium-term planning although they might need contextual adaptation to reflect operational and logistical constraints that are not well reflected in theory.

Cost-effectiveness models are particularly useful in the resources-constrained setting where economic sustainability forms the core of decision-making. These models are used in the decisions of government budgets and donor funds by comparing the health gains with the financial investments. These models are especially applicable in the evaluation of integrated intervention packages or elimination-based interventions. Their inferences, however, depend on sound cost information and assumptions on health system performance.

On the whole, the modelling framework must be based on the context of the decision. Transmission and intervention models can be the most informative in high-burden settings that center on the reduction of morbidity and mortality. In lower-transmission or transitional settings, long-term elimination planning could be served more effectively by optimisation and economic assessment frameworks. Biological, operational, and economic perspectives enhance the policy relevance of the modelling outputs and contribute to the malaria control in SSA.

Roles of modelling in policy and decision making

The role of mathematical modelling in influencing national decision-making in recent global malaria

initiatives is increasing. The High Burden to High Impact program and the Surveillance as a Core Intervention framework are some of the programs that advocate the utilization of data-driven strategies to enhance malaria control measures. In such initiatives, modelling outputs are frequently used together with surveillance data and programmatic information to aid intervention prioritization, assess potential strategies, and national malaria control planning in endemic countries.

Limitations of the review

The main emphasis in this review was on epidemiological models that are published in peer-reviewed scientific publications. As a result, the modelling methods mentioned in National Malaria Control Programme (NMCP) reports and strategic plans among other operational reports were not listed systematically. These models can be especially powerful, because they are frequently used directly to shape national malaria control policies and decisions of resource allocation.

Besides this, the review was also limited to English-language publication. Relevant studies that were published in other languages might hence have been missed. In the same manner, the review did not include editorials, commentaries, opinion papers, preprints, and other types of grey literature, which might reflect emerging modelling methods or programmatic observations which are not yet reflected in peer-reviewed articles.

The search was restricted to studies published up to 31 December 2024, hence more recent modelling developments were not covered. In addition, the review was specifically focused on studies carried out in SSA. Although this was necessary in order to meet the study objectives, this excludes modelling approaches that have been developed in other regions, which can also be applicable or adapted to the malaria transmission settings in the region.

The other limitation is associated with the model inclusion criteria. Only studies that included both human and vector components were considered. Although this methodology guaranteed the models to capture important dynamics of transmission, it might have been biased towards studies that covered particular aspects of malaria epidemiology, including purely vector ecological models or purely human transmission studies.

In addition to the models included in this review, there are also large-scale malaria modelling platforms which have been extensively used to aid in global and country-level malaria decision-making. These include EMOD, malariasimulation and OpenMalaria. They are used widely in large scientific studies of collaborative modelling, and policy analysis to assess and evaluate intervention strategies and inform malaria control planning.

These platforms typically contain comprehensive epidemiological, demographic, and intervention data, and are commonly combined with global malaria efforts and national malaria control programs. Although these modelling systems did not form the main target of this review, it is necessary to take note of their place in offering a wider context to the modelling landscape in SSA.

Discussion

This systematic review is a synthesis of epidemiological models that are used to study the transmission of malaria in sub-Saharan Africa (SSA). The review included 102 modelling studies, which demonstrated substantial methodological diversity but also demonstrated clear trends in how the malaria transmission has been studied in the area. Most studies (52.9%) were transmission-focused, followed by intervention models (21.6%), cost-effectiveness models (15.7%), and optimal control models (9.8%). This suggests that the research on malaria modelling in SSA has mostly focused on the dynamics of transmission, instead of considering the strategies of policy implementation.

Transmission-based models predominate because it is important to still understand the biological and ecological processes that support the malaria transmission in endemic environments. Environmental drivers included temperature, rainfall, and seasonality used in many studies that have a strong impact on the mosquito life cycle and the development of parasites. The models have played a significant role in discovering major drivers of the transmission and predicting the possible variations upon changes in the environmental conditions. Nevertheless, unlike useful theoretical insights, these models are sometimes not explicitly represented by real-world intervention situations, which restricts their direct use in the process of operational malaria control planning.

The framework offered by intervention-driven models is more policy relevant since it specifically considers the effectiveness of malaria control programs like insecticide-treated nets (ITNs), indoor residual spraying (IRS), treatment programs, and vaccination. Such models enable policymakers to model the possible impacts of the scaling up of various interventions or the application of some strategies in the context of various epidemiological settings. However, the outcomes of intervention models frequently rely on assumptions about the coverage of interventions, their adherence, and sustainability in the long term, which might not correspond to those of programmatic interventions in SSA.

Another important modelling approach is optimal control models, which combine mathematical optimization methods to find the most efficient choice or

time of interventions. The models find specific uses in resource-constrained environments where policymakers have to distribute scarce resources to competing priorities in the domain of public health. Nevertheless, a large number of the optimal control models remain theoretical and might need additional modification to include practical constraints of implementation, including logistical capacity and behavioural responses.

Cost-effectiveness models are epidemiological modelling that involves economic factors in decision-making. The models are particularly useful in situations where governments and funding organizations have to maximize health benefits by limited funding. The cost-effectiveness analyses are the critical insights into the sustainability of malaria control programmes in the long term in comparison to the intervention costs and epidemiological outcomes. Although they are important, the number of studies in the review that identified cost-effectiveness modelling is rather low.

Within all the model types, a number of significant gaps in research were found. To begin with, drug resistance or insecticide resistance was only explicitly included in relatively few models, although their role in malaria control is becoming increasingly important. Second, the human mobility and migration that can contribute to the reintroduction of infections into the low-transmission environment was only covered in a few studies. Third, asymptomatic and submicroscopic infections are frequently underreported in modelling studies due in large part to routine surveillance data in many SSA countries only reflecting symptomatic cases identified in the health service.

The use of data availability and quality is another important limitation that has been found in studies. A large number of modelling studies are based on regular data in a health system or international reporting systems like the World Health Organization. Complete routine surveillance data is often not available in most SSA countries and especially within the private health sector. Moreover, the sources of asymptomatic infections are hardly recorded in standard reporting mechanisms which can result in underreporting the actual degree of transmission in an endemic environment.

In spite of these constraints, epidemiological modelling is a vital tool for malaria research and policy planning. Models can facilitate evidence-based decision-making in malaria control programmes by offering a framework to investigate hypothetical situations and assess intervention policies and predict future trends. Close collaboration between modellers, epidemiologists and national malaria control programmes will be essential to make sure that the results of the modelling processes are in line with the operational requirements.

Future modelling attempts should thus focus more on the integration of epidemiological, environmental and socio-economic variables and also should be more realistic in representing resistance dynamics, human movements as well as the asymptomatic infections. More transparency, open-source modelling frameworks and utilization of locally calibrated data will further make malaria models in SSA more policy relevant and applicable.

Conclusion

This systematic review demonstrates how malaria epidemiological modelling in SSA relies on both strict methodology and practical applications. Through grouping the studies into four main groups, the review offers researchers and policy-makers a clear framework to assess modelling techniques based on their context and question. Mathematical modelling systems for malaria control should consider variations in climate, the rise of resistance in drugs and insecticides, diverse forms of immunity and human movements. Despite deterministic models continuing to be the most widely utilized method, stochastic models, spatial models and agent-based models are being used more actively in malaria studies and have the benefit of dealing with uncertainty, fine-scale variability, and regional heterogeneity in the planning of intervention.

While modelling has advanced, more precise work is needed to meet evolving government requirements. Models should consider cultural contexts, encourage cross-disciplinary collaboration, and use open-source methods. These steps will strengthen malaria knowledge and improve the reach of control efforts.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12936-026-05870-8>.

Additional file1 (DOCX 24 kb)
Additional file2 (DOCX 17 kb)
Additional file3 (DOCX 467 kb)
Additional file4 (PDF 499 kb)
Additional file5 (PDF 254 kb)
Additional file6 (PDF 111 kb)
Additional file7 (DOCX 13 kb)
Additional file8 (XLSX 96 kb)

Author contributions

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Data availability

The systematic review utilized data from authorized published publications that are publicly accessible online.

Declarations

Ethics approval and consent to participate

Primary data collection and human participants did not play any role in this systematic review. Since the study did not include human participants or primary data collection the need for informed consent and ethical approval became irrelevant.

Competing interests

The authors declare no competing interests.

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