Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Modelling the effects of seasonal malaria chemoprevention 1on malaria transmission dynamics in the presence of existing interventions in Nigeria

Oluwaseun Akinlo Mogbojuri
Adekunle Ajasin University
Emmanuel Afolabi Bakare
emmanuel.bakare@fuoye.edu.ng
Federal University Oye Ekiti
Olusola Oresanya
Malaria Consortium
Lukman Shina Akinola
Federal University Oye Ekiti
Afeez Abidemi
Federal University of Technology
Idowu Isaac Olasupo
Federal University Oye Ekiti
Samuel Abidemi Osikoya
Federal University Oye Ekiti
Nwana Onyebuchi Aaron
Federal University Oye Ekiti
Dolapo Oluwaseun Oniyelu
Federal University Oye Ekiti
Nelson Eze
National Malaria Elimination Programme

Research Article

Keywords: Malaria, Seasonal malaria chemoprevention, Parameter estimation, Sensitivity analysis, Mathematical modelling, Nigeria

Posted Date: July 7th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10163934/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Modelling the effects of seasonal malaria chemoprevention on malaria transmission dynamics in the presence of existing interventions in Nigeria

Oluwaseun Akinlo Mogbojuri[1,2,3], Emmanuel Afolabi Bakare[1,2,*], Olusola Oresanya[4], Lukman Shina Akinola[2], Afeez Abidemi[1,5], Idowu Isaac Olasupo[1,2], Samuel Abidemi Osikoya [1,2], Aaron Onyebuchi Nwana [1,6], Dolapo Oluwaseun Oniyelu[1,7], Nelson Eze[8]

1 International Centre for Applied Mathematical Modelling and Data Analytics, Federal University Oye-Ekiti, Ekiti State, Nigeria
2 Department of Mathematics, Federal University Oye-Ekiti, Ekiti State, Nigeria
3 Department of Mathematical Sciences, Adekunle Ajasin University, Akungba-Akoko, Nigeria
4 Malaria Consortium, Maitama, Abuja, Nigeria
5 Department of Mathematical Sciences, Federal University of Technology, Akure, Ondo State, Nigeria
6 Department of Animal and Environmental Biology, Federal University Oye-Ekiti, Ekiti State, Nigeria
7 Department of Computer Science, Federal University Oye-Ekiti, Ekiti State, Nigeria
8 National Malaria Elimination Programme, Abuja, Nigeria

*__Correspondence:__ emmanuel.bakare@fuoye.edu.ng

Abstract

Background: Seasonal malaria chemoprevention (SMC) is the intermittent administration of sulfadoxine-pyrimethamine plus amodiaquine to children (between age 3 and 59 months) at high risk of severe malaria living in areas with seasonal transmission during the period when malaria transmission is highest. In 2025, SMC had been implemented in 21 Nigerian states (including the Federal Capital Territory) where malaria transmission is intense and highly seasonal. This study assessed the overall population level impact of SMC beyond the targeted population on malaria dynamics in six implementing states in Nigeria.

Methods: A deterministic compartmental model that captured the SMC-administered population was formulated. The model incorporates long-lasting insecticide treated nets (LLINs) and artemisinin-based combination therapy (ACT) as baseline interventions. The model was fitted to routine malaria data (January 2015 - December 2024) and SMC coverage data from Bauchi, Yobe, Kebbi, Zamfara, Plateau and Nasarawa States using the nonlinear least squares method. Uncertainties in the estimated parameters and model trajectories were quantified using a parametric bootstrap method. Global sensitivity analysis (GSA) was performed to identify key drivers of malaria prevalence across the six study states.

Results: The estimated reduction in confirmed uncomplicated malaria cases over post-SMC implementation period in the six states ranged from 14.5% (95% CI: 9.6 – 20.7%) in Nasarawa to 26.9 % (95% CI: 23.6 – 39.8%) in Yobe. GSA showed that malaria prevalence is primarily driven by vector-related parameters. The mosquito biting rate,

mosquito recruitment rate, and transmission probabilities between mosquitoes and humans were strongly positively correlated with malaria prevalence, whereas the mosquito natural mortality rate showed a strong negative correlation, suggesting that increased mosquito mortality can significantly reduce malaria. Further analysis suggests that while increasing SMC coverage consistently leads to decline in malaria cases, its effectiveness is strongly affected by high mosquito biting rates and low mosquito mortality.
Conclusion: The findings demonstrate that SMC significantly lowers malaria morbidity beyond the targeted population, with varying impact across states. However, its effectiveness is strongly dependent on underlying vector dynamics. Integrating SMC with complementary vector control interventions such as LLINs or indoor residual spray (IRS) that reduce mosquito biting and increase mosquito mortality is essential to achieve sustained malaria control in high-transmission settings.

Keywords: Malaria, Seasonal malaria chemoprevention, Parameter estimation, Sensitivity analysis, Mathematical modelling, Nigeria

1 Background

Malaria is a vector-borne disease transmitted through the bite of infected female adult Anopheles mosquitoes [1]. It remains a major public health challenge, particularly in sub-Saharan Africa, where the burden of disease is disproportionately high [2]. In 2022, an estimated 249 million malaria cases and 608,000 deaths were reported globally, with over 95% occurring in Africa [3]. Children under five years of age bear the greatest burden, accounting for the majority of malaria-related mortality in the region [2]. The disease is highly seasonal in the Sahel and parts of northern Nigeria, where a large proportion of annual cases occur within a few months of the rainy season [4].

Nigeria carries the highest malaria burden globally, contributing approximately 27% of global cases and 31% of deaths [5]. Malaria transmission occurs throughout the country, with marked spatial and seasonal heterogeneity, ranging from perennial transmission in the south to highly seasonal transmission in the northern regions [6]. Despite sustained malaria control efforts by the National Malaria Elimination Programme, including chemoprevention, long-lasting insecticidal nets (LLINs), and improved case management, malaria remains a leading cause of mortality, particularly among children under five years of age [7].

Seasonal malaria chemoprevention (SMC) has emerged as a key intervention for reducing malaria burden in areas with highly seasonal transmission [8]. Recommended by the World Health Organization in 2012, SMC involves the intermittent administration of sulfadoxine-pyrimethamine plus amodiaquine (SPAQ) to children aged 3–59 months during peak transmission periods [8]. Clinical and observational studies have demonstrated that SMC can reduce malaria incidence in this target group by up to 75% when administered monthly during the transmission season [9, 10].

In Nigeria, SMC was introduced in 2014 following successful pilot implementation in 2013 and has since been scaled up substantially, reaching millions of children annually across eligible states [11]. Recent programme reports indicate expansion to 21 states (including the Federal Capital Territory), with increasing coverage and operational scale [12]. During each SMC cycle, treatment is administered over three consecutive days. Community drug distributors (CDDs) deliver the first dose through door-to-door visits, after which the remaining doses are left with caregivers for administration on the second and third days [11, 13]. Two dosing regimens of sulfadoxine–pyrimethamine plus amodiaquine (SPAQ) are used based on age. SPAQ 1, consisting of 250 mg/12.5 mg of SP and 75 mg of AQ, is administered to infants aged 3-11 months, while SPAQ 2, comprising 500 mg/25 mg of SP and 150 mg of AQ, is given to children aged 12-59 months [14, 15].

Mathematical modelling provides a powerful framework for investigating the transmission dynamics of infectious diseases and evaluating the potential impact of intervention strategies under different scenarios [16]. In the context of malaria, mechanistic models have been widely used to simulate

malaria transmission dynamics and assess the effectiveness of control interventions [17]. Several modelling studies have applied mathematical frameworks to Nigerian data to explore malaria transmission dynamics and evaluate intervention impacts [18, 19, 20, 21, 22].

Existing studies on SMC in Nigeria and other parts of sub-Saharan Africa have largely focused on SMC's effectiveness in reducing malaria incidence among children under 5, using clinical trials, observational studies, and statistical analyses [23, 24, 25, 26, 27]. While SMC's effectiveness in reducing malaria incidence in children 3-59 months has been well-established in these studies, the public health impact on the broader population beyond the targeted children has largely remain unknown. Furthermore, existing studies assessing SMC's impact in Nigeria, to our knowledge do not explicitly capture the transmission dynamics of malaria in the country.

This study therefore aims to fill this gap by assessing and quantifying the effectiveness of SMC in the presence of existing interventions on malaria burden across the entire population in six implementing states in Nigeria. Specifically, the study addresses two research questions. First, to what extent has SMC reduced malaria cases across the general population in selected SMC-implementing states in Nigeria? Second, which epidemiological factors influence the effectiveness of SMC in reducing malaria transmission and case burden in selected SMC-implementing states in Nigeria? To address these questions, a deterministic compartmental model was developed and fitted to malaria incidence data from six SMC-implementing states in Nigeria. The model is used to quantify the impact of SMC on malaria morbidity under observed and counterfactual scenarios, and to explore the sensitivity of transmission dynamics to key epidemiological parameters.

The remainder of the paper is structured as follows. The Materials and Methods section describes the study area, data sources, and modelling framework. The Model Parameterization section outlines the estimation of model parameters and initial conditions. The Results section presents the main findings, followed by a Discussion of their implications. Finally, the Conclusion summarizes the key contributions of the study.

2 Materials and methods

2.1 Study setting

The study is focused on 6 states out of the 21 states where SMC is currently being implemented in Nigeria. The 6 states are drawn from the three main geo-political zones in Nigeria where SMC is being implemented. The selected states include: Bauchi and Yobe in North-East Nigeria; Kebbi and Zamfara in North-West Nigeria; and Plateau and Nasarawa in North-Central Nigeria. These states were selected in the 3 Northern geopolitical zones due to their high malaria prevalence in children according to WHO [28]. Furthermore, Plateau, Nasarawa and Bauchi were also chosen for their five-cycle SMC implementation.

Bauchi State, located in the North-Eastern geopolitical zone of Nigeria borders Kano and Jigawa to the north, Taraba and Plateau to the south, Gombe and Yobe to the east, and Kaduna to the west [28]. In 2015, Bauchi's estimated population was 6,603,199 [29]. SMC was first introduced in Bauchi State in 2020 with four monthly cycles. By 2022, the number of cycles had increased to five in ten local government areas [11, 30].

Yobe State, also located in the North-Eastern zone of Nigeria borders the Republic of Niger to the north, Borno and Adamawa to the east and south [28]. The State's estimated population was 3,067,883 in 2015 [29]. Yobe State experiences two distinct seasons: the dry season (October/November to April/May) and the rainy season (May/June to September/October), with mean annual rainfall of around 547.2 millimeters [28]. SMC was first launched in Yobe in 2019 in only 6 LGAs with full coverage starting in 2020 [11, 31].

Kebbi State is located in Nigeria's North-Western Region. It shares borders with Sokoto and Zamfara to the east and north, Niger to the south, and the Republic of Benin and the Republic of Niger to

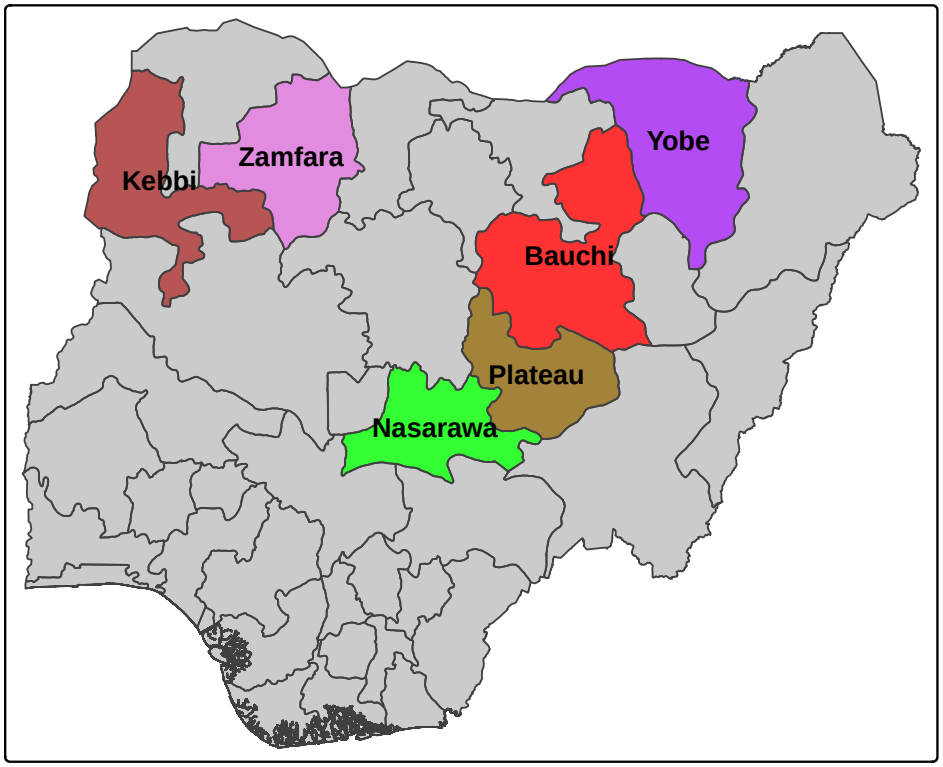


Figure 1: ***Map of Nigeria showing the six selected states. The map was generated using shapefiles and geospatial data, processed and visualized with R software.***

the west. According to estimates, the State's population was 4,377,770 in 2015 [29]. The State has two distinct seasons: the dry season from November to March and the rainy season from April to October, with an average annual rainfall of approximately 845.9 millimeters [28]. SMC, with four monthly cycles was introduced in Kebbi State in 2020 [28, 31].

Zamfara State is located in the North-Western Region of Nigeria. It borders the Republic of Niger to the north, Kaduna to the south, Katsina to the east, and Sokoto, Kebbi and Niger States to the west [28]. The State's estimated population was 4,686,636 in 2015 [29]. The State experiences two distinct seasons: the dry season (October to April) and the rainy season (May to September) with annual rainfall averaging around 813.6 millimeters [28]. SMC was first implemented in Zamfara State in 2015 reaching only seven local governments with four monthly cycles [28].

Plateau State is located in the North-Central Region of Nigeria. It is bordered by Bauchi to the northeast, Kaduna to the northwest, Nasarawa to the southwest, and Taraba to the southeast [28]. In 2015, the estimated population of the State was 4,005,406 [29]. The State has two distinct seasons: the dry season from September to April and the rainy season from May to August. The average annual rainfall is approximately 1,042.7 millimeters [28]. SMC was introduced in Plateau in 2021 with five monthly cycles [30, 31].

Nasarawa State is located in Nigeria's North-Central Region. To the east, it is bordered by Taraba and Plateau; to the north, by Kaduna; to the south, by Kogi and Benue; and to the west, by the Federal Capital Territory [28]. In 2015, the State's estimated population was 2,347,955 [29]. The State has two distinct seasons: the dry season from November to February and the rainy season from March to October with an average annual rainfall of approximately 1,217.4 millimeters [28]. Five monthly cycles of SMC were implemented in Nasarawa in 2022 [30]

2.2 Data description

Monthly reported malaria cases data for the selected states spanning a period of ten years from January 2015 to December 2024 was considered. Additionally, SMC coverage data from the start of implementation in each state up to 2024 was used. The data were obtained from the National Malaria Data Repository (NMDR) owned by NMEP. The monthly reported malaria cases data contains 120 observations and 14 variables which includes information such as number of children aged 3-59 months who received SP+AQ, confirmed uncomplicated malaria, severe malaria cases etc.

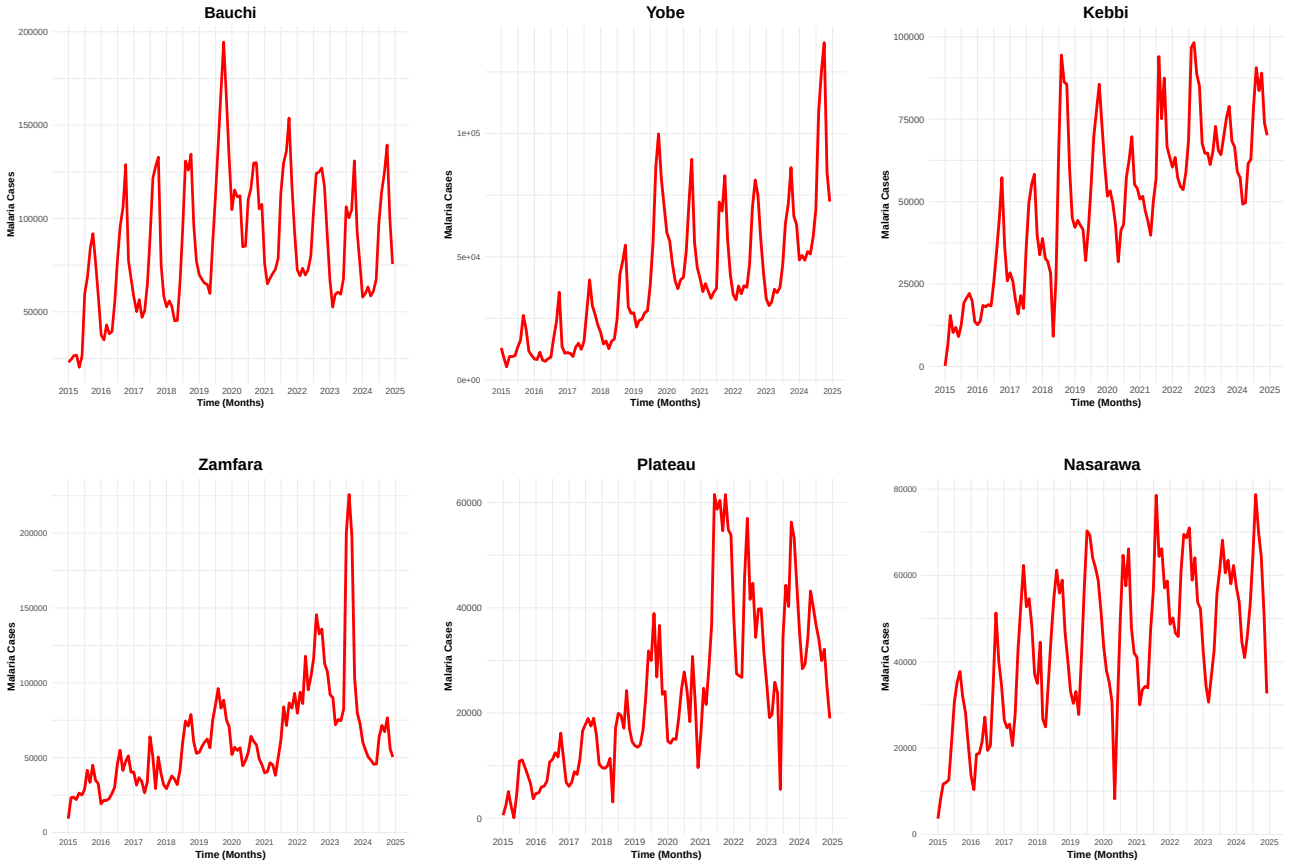


Figure 2: Time series plots of confirmed uncomplicated malaria cases in Bauchi, Yobe, Kebbi, Zamfara, Plateau and Nasarawa States from January 2015 to December 2024.

2.3 Model description and formulation

A deterministic, compartmental $S_hM_cE_hA_hI_hS_h-S_vE_vI_v$ model that incorporates the SMC-administered class is developed. The model is stratified into two major sub-groups: the human population and the mosquitoes population, both divided into mutually exclusive compartments. The population of human is divided into susceptible human $S_h(t)$, SMC-administered children $M_c(t)$, pre-infectious human $E_h(t)$, asymptomatic infectious human $A_h(t)$, and symptomatic infectious human $I_h(t)$. The mosquito population is divided into susceptible mosquitoes $S_v(t)$, pre-infectious mosquitoes $E_v(t)$ and infectious mosquitoes $I_v(t)$.

Thus, the total human population at any time t, denoted by $N_h(t)$, is given as,

$$N_h(t) = S_h(t) + M_c(t) + E_h(t) + A_h(t) + I_h(t). \tag{2.1}$$

And the total mosquito population at any time t, denoted as $N_v(t)$, is given as

$$N_v(t) = S_v(t) + E_v(t) + I_v(t). \tag{2.2}$$

We assume that recruitment into the susceptible class S_h is through birth at a rate Λ_h. Since SMC treatment is targeted at children between age 3-59 months, eligible children transit from the susceptible human compartment to the SMC-administered compartment at the rate ξ_t. SMC treatment wanes at rate η and children in SMC-administered class become susceptible again at that rate. Symptomatic individuals, after being treated with ACT recover and return to being susceptible again. The population of susceptible humans gets depleted when susceptible individuals become infected at a rate

$$\lambda_h(t) = (1-u)\frac{b(t)\beta_{vh}I_v}{N_h},$$

where $(1-u)$, $(0 \leq u < 1)$ denotes the reduction in transmission as a result of LLIN, and β_{vh} is the probability of transmission from an infectious female Anopheles mosquito to a susceptible human. $b(t)$ is the seasonally forcing function introduced in the mosquito biting rate in order to account for the seasonal patterns observed in the data, and is given as

$$b(t) = b_0\left(1 + b_1\cos\left(\frac{2\pi(t-\phi)}{12}\right)\right), \tag{2.3}$$

where b_0 is the baseline biting rate of mosquitoes, b_1 is the amplitude and ϕ is the phase shift. The susceptible human population further decreases due to natural death at rate μ_h. Thus, the rate of change of the susceptible human population at any given time t is given as

$$\frac{dS_h}{dt} = \Lambda_h - (\lambda_h(t) + \xi_t + \mu_h)S_h + \eta M_c + \alpha I_h. \tag{2.4}$$

Recruitment into the SMC-administered class comes from three sources, the susceptible class, the pre-infectious class and the asymptomatic class. We let $S_h + E_h + A_h$ be the total population of humans who are susceptible, pre-infectious or asymptomatic infectious. Only a fraction of these individuals (children aged 3-59 months) are eligible for SMC treatment. We denote this fraction by f, $0 < f < 1$. Thus, the number of eligible children at time t is given by $P_c = f(S_h + E_h + A_h)$. Given that SMC is administered at a coverage rate of ψ_t, then the recruitment rate into the SMC-administered class is given by $\xi_t = f\psi_t$. The protective effectiveness of SMC treatment wanes off (due to poor adherence to the 3-day regimen, poor administration, drug quality, or drug resistance [23]) and eligible children leave the SMC class at a rate η and become susceptible again. Since SMC does not confer 100% protection, children in the SMC class can still become infected, albeit at a reduced rate $(1-\tau)\lambda_h(t)$ and transit to the pre-infectious class. The parameter $(1-\tau)$, $0 < \tau < 1$, reduces the transmission of the parasite from an infectious female Anopheles mosquito to children in the SMC compartment. $\tau = 1$, implies that SMC treatment offers perfect protection, and no child in the SMC-administered class will be infected. On the other hand, if $\tau = 0$, then SMC provides no protection, and children in the SMC-administered class have the same rate of infection as the individuals in the susceptible class. The population of SMC treated class is further reduced through natural death of children between 3-59 months. Thus, the rate of change of SMC-administered class is given as

$$\frac{dM_c}{dt} = \xi_t(S_h + E_h + A_h) - [(1-\tau)\lambda_h(t) + \eta + \mu_h]M_c. \tag{2.5}$$

Inflow into the pre-infectious class occurs when susceptible humans and children in SMC class get infected at rates $\lambda_h(t)$ and $(1-\tau)\lambda_h(t)$ respectively. Individuals remain in the pre-infectious compartment for an average duration $\frac{1}{\rho_h}$ (the period of time when sporozoites transform into merozoites inside the human liver). A proportion q of the pre-infectious human transit to the symptomatic compartment while the remaining proportion $(1-q)$ progress to the asymptomatic compartment. The pre-infectious compartment is further reduced via natural death and when eligible children in that class get SMC treatment and move into the SMC treated class at rate ξ_t. The rate of change of the pre-infectious class is thus given as

$$\frac{dE_h}{dt} = \lambda_h(t)S_h + (1-\tau)\lambda_h(t)M_c - (\xi_t + \rho_h + \mu_h)E_h. \tag{2.6}$$

The asymptomatic compartment is increased when a proportion $(1-q)$ moves from the pre-infectious class and become asymptomatic at the rate ρ_h. The asymptomatic infectious population is depleted as a result of more infectious bites and thus becoming symptomatic at rate $\gamma\lambda_h(t)$, and via natural death at rate μ_h. Furthermore, eligible children in the asymptomatic compartment get SMC treatment and transit to SMC class at rate ξ_t. Thus, the rate of change of the asymptomatic infectious population at time t is given as

$$\frac{dA_h}{dt} = (1-q)\rho_h E_h - (\gamma\lambda_h(t) + \xi_t + \mu_h)A_h. \tag{2.7}$$

Similarly, the symptomatic infectious compartment is increased when a proportion q transit from the pre-infectious class and become symptomatic at rate ρ_h. The population of symptomatic infectious human is further increased when asymptomatic individuals get more infectious bites and become symptomatic at rate $\gamma\lambda_h(t)$. Individuals in the symptomatic infectious class recover due to treatment at rate α and subsequently return to the susceptible class. Furthermore, the symptomatic infectious class is reduced due to malaria induced mortality at rate δ and natural death at rate μ_h. Consequently, the rate of change of the symptomatic infectious population at time t is given as

$$\frac{dI_h}{dt} = q\rho_h E_h + \gamma\lambda_h(t)A_h - (\alpha + \mu_h + \delta_h)I_h. \tag{2.8}$$

Female *Anopheles* mosquitoes (male mosquitoes are excluded from the transmission dynamics since they do not feed on blood meals) are recruited into the susceptible compartment through birth at rate Λ_v. Susceptible female *Anopheles* mosquitoes transit to the pre-infectious class (after biting either a symptomatic or asymptomatic infectious human and ingesting parasites called gametocytes) at rate

$$\lambda_v(t) = (1-u)\frac{b(t)\beta_{hv}(\sigma I_h + A_h)}{N_h},$$

where β_{hv} is the probability of transmission from an infectious human to a susceptible mosquito. The parameter σ $(0 < \sigma < 1)$ accounts for the reduced infectivity of symptomatic individuals relative to asymptomatic individuals, due to typically lower mature gametocyte densities in symptomatic infections [32, 33]. The population is further depleted due to natural death at rate μ_v. Thus, the rate of change of the susceptible mosquito population is given as

$$\frac{dS_v}{dt} = \Lambda_v - (\lambda_v(t) + \mu_v)S_v. \tag{2.9}$$

The pre-infectious female *Anopheles* mosquito compartment is increased when susceptible female *Anopheles* mosquito become infected at rate $\lambda_v(t)$. Pre-infectious mosquitoes remain in the pre-infectious class for a (latent) period of about 10-18 days before sporozoites (another form of the parasites) migrate to the mosquitoes' salivary gland [1] when the mosquitoes becomes infectious. Thus, this population is depleted when pre-infectious female *Anopheles* mosquito either become infectious, progressing to the infectious female *Anopheles* mosquito compartment at a rate ρ_v, or die naturally at a rate μ_v. Consequently, the rate of change of the population of pre-infectious female mosquito is given as

$$\frac{dE_v}{dt} = \lambda_v(t)S_v - (\rho_v + \mu_v)E_v. \tag{2.10}$$

The infectious female *Anopheles* mosquito compartment increases as pre-infectious mosquitoes progress to the infectious stage at a rate ρ_v. It decreases due to natural death at a rate μ_v. Therefore, the rate of change of the infectious female *Anopheles* mosquito population is given by:

$$\frac{dI_v}{dt} = \rho_v E_v - \mu_v I_v. \tag{2.11}$$

The model used to investigate the transmission dynamics of malaria in this study is described by the systems of nonlinear differential equations given in equation (2.12).

$$\begin{aligned}
\frac{dS_h}{dt} &= \Lambda_h - (\lambda_h(t) + \xi_t + \mu_h)S_h + \eta M_c + \alpha I_h,\\
\frac{dM_c}{dt} &= \xi_t(S_h + E_h + A_h) - [(1-\tau)\lambda_h(t) + \eta + \mu_h]M_c,\\
\frac{dE_h}{dt} &= \lambda_h(t)S_h + (1-\tau)\lambda_h(t)M_c - (\xi_t + \rho_h + \mu_h)E_h,\\
\frac{dA_h}{dt} &= (1-q)\rho_h E_h - (\gamma\lambda_h(t) + \xi_t + \mu_h)A_h,\\
\frac{dI_h}{dt} &= q\rho_h E_h + \gamma\lambda_h(t)A_h - (\alpha + \delta_h + \mu_h)I_h,\\
\frac{dS_v}{dt} &= \Lambda_v - (\lambda_v(t) + \mu_v)S_v,\\
\frac{dE_v}{dt} &= \lambda_v(t)S_v - (\rho_v + \mu_v)E_v,\\
\frac{dI_v}{dt} &= \rho_v E_v - \mu_v I_v.
\end{aligned} \tag{2.12}$$

Subject to the following initial conditions:

$$S_h(0) > 0, M_c(0) > 0, E_h(0) \geq 0, I_h(0) > 0, A_h(0) > 0, S_v(0) > 0, E_v(0) \geq 0, I_v(0) > 0. \tag{2.13}$$

The time-dependent forces of infection $\lambda_h(t) := \lambda_h(t)$ and $\lambda_v(t) := \lambda_v(t)$ for human and mosquitoes populations are respectively given as:

$$\lambda_h(t) = (1-u)\frac{b(t)\beta_{vh}I_v}{N_h}, \qquad \lambda_v(t) = (1-u)\frac{b(t)\beta_{hv}(\sigma I_h + A_h)}{N_h}. \tag{2.14}$$

The complete description of the state variables and parameters of model (2.12) is given in Table 1 while the schematic diagram is depicted in Figure 3.

3 Model parameterization and initial conditions

In this section, we describe the process of obtaining all parameter values and initial conditions of model 2.12 used in this study. The model has a total of 22 parameters. Some parameters were derived from the demographic data of each state, others from malaria epidemiological information and existing literature, while the remaining parameters were estimated using malaria incidence and SMC coverage data from each of the six states. The fixed baseline parameters are presented in Table 2 while the estimated parameters are presented in Tables 3 and 4.

3.1 Demographic parameters

The natural death rates for human and mosquito are given as $\mu_h = (\text{average human lifespan})^{-1}$ and $\mu_v = (\text{average mosquito lifespan})^{-1}$ respectively. The average lifespan of human in 2015 for each of the six states is given as 50.9 years = 610.8 months for Bauchi, 48.6 years = 583.2 months for Yobe, 56.5 years = 678 months for Kebbi, 54.8 years = 657.6 months for Zamfara, 49.8 years = 597.6 months for Plateau and 54.3 years = 651.6 months for Nasarawa. Thus, μ_h is given as 0.00164 per months (Bauchi), 0.00171 per months (Yobe), 0.00147 per month (Kebbi), 0.00152 per months (Zamfara), 0.00153 per months (Nasarawa) and 0.00167 per months (Plateau). The average lifespan of female

Table 1: Description of Variables and Parameters.

Variable	**Description**
S_h, S_v	Population of susceptible human and susceptible female Anopheles mosquitoes
M_c	Population of SMC-administered children
E_h, E_v	Population of pre-infectious human and pre-infectious female Anopheles mosquitoes
I_h, I_v	Population of symptomatic infectious human and infectious female Anopheles mosquitoes
A_h	Population of asymptomatic infectious human
Parameter	**Description**
Λ_h, Λ_v	Recruitment rates into human and mosquito population respectively
β_{vh}	Probability that a bite results in transmission of sporozoites from an infectious mosquito to a susceptible human
β_{hv}	Probability that a blood meal results in transmission of gametocytes from an infectious human to a susceptible mosquito
τ	Protective effectiveness of SMC treatment
b_0	Baseline biting rate of mosquitoes
ψ_t	Rate at which children are administered SMC
η	SMC treatment waning rate
ρ_h, ρ_v	Rates at which pre-infectious human and mosquitoes respectively become infectious
f	Proportion of human that are eligible for SMC treatment
α	Recovery rate of symptomatic human due to treatment
q	Proportion of pre-infectious human that become symptomatic upon infection
$(1-q)$	Proportion of pre-infectious human that become asymptomatic upon infection
σ	Reduction of infectivity from symptomatic human to susceptible mosquito
μ_h, μ_v	Natural death rates
δ_h	Disease induced death rate
u	Protective effectiveness of LLINs
γ	Probability of asymptomatic individuals becoming symptomatic due to more infectious bi
b_1	Amplitude
ϕ	Phase shift.

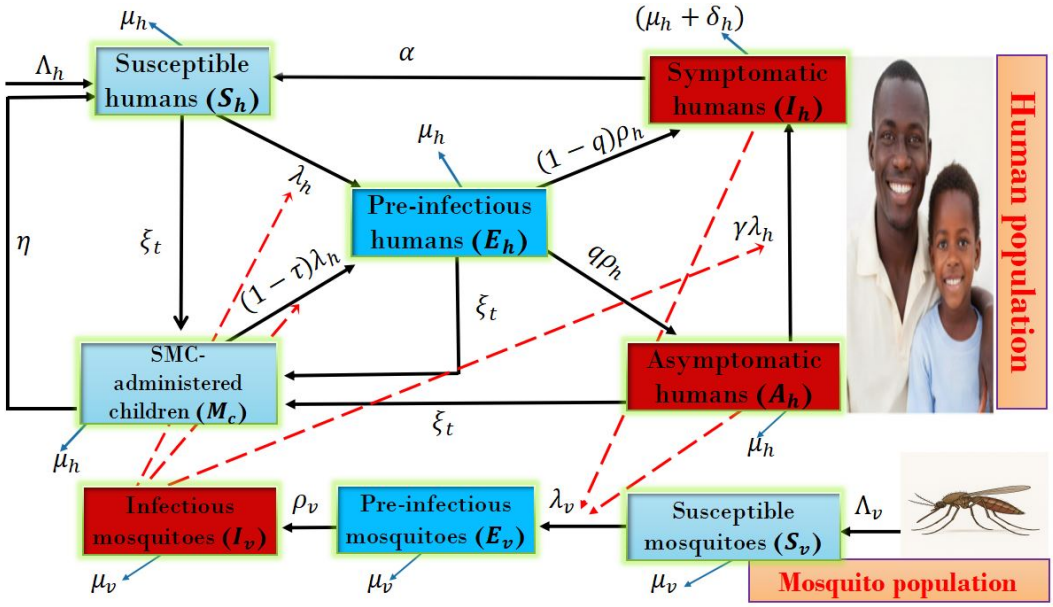


Figure 3: ***Schematic diagram for malaria transmission between human population and mosquitoes****. The black solid arrows show the transition of human and mosquitoes through the different stages of malaria disease at the rates indicated beside the arrows, the light blue solid arrows indicate deaths due to malaria, and red dashed arrows indicate disease transmission.*

Anopheles mosquitoes is taken to be 15 days = 0.5 months [1]. Hence, μ_v is given as 2 per months for each of the six states. We assume a constant human and mosquito recruitment rates computed using the formula $\Lambda_h = \mu_h \times N_h(0)$ and $\Lambda_v = \mu_v \times N_v(0)$ respectively, where $N_h(0)$ and $N_v(0)$ are the respective initial total human and female *Anopheles* mosquito populations for each state. We also assume that the initial population size of female *Anopheles* mosquitoes is three times that of humans, i.e, $N_v(0) = 3 \times N_h(0)$. Thus, by taking the product of initial population size in 2015 for each of the states as presented in subsection 2.1 and μ_h for each state, the human recruitment rate is given as follows: 10,829.25 per month (Bauchi), 5,246.08 per month (Yobe), 6,435.32 per month (Kebbi), 7,123.69 per month (Zamfara), 3592.37 per month (Nasarawa) and 6689.03 per month (Plateau). Similarly, the mosquito recruitment rates for Bauchi, Yobe, Kebbi, Zamfara, Nasarawa and Plateau are respectively computed as 39,619,194 mosquito per month, 18,407,298 mosquito per month, 26,266,620 mosquito per month, 28,119,816 mosquito per month, 14,087,730 mosquito per month and 24,032,436 mosquito per month.

3.2 Malaria epidemiological parameters

The latent period ($\frac{1}{\rho_h}$) of *P. falciparum* malaria in humans is given as 10 days = $\frac{1}{3}$ months [34]. Thus, the rate at which pre-infectious humans progress to being infectious, $\rho_h = 3$ per month across the six states. Similarly, with latent period ($\frac{1}{\rho_v}$) of *P. falciparum* malaria in mosquitoes given as 11 days = $\frac{11}{30}$ months [34], ρ_v is taken as 2.727 per months. The recovery rate due to ACT is given by $\alpha = -\frac{\log_e(1-p)}{\Delta t}$ where p is the product of the efficay of ACT (ϵ_a) and ACT treatment coverage (c_a), and Δt is the time taken for ACT to clear the parasite from the blood. We set $\Delta t = 28$ days $= 0.93$ months which is the minimum follow-up days during therapeutic efficacy studies (TES) for artemether-lumefantrine (AL), the frontline treatment for uncomplicated *Pf* malaria in Nigeria [35]. We take $\epsilon_a = 96\%$ to be the average efficacy of ACT treatment in Nigeria [36]. For each of the six states, we obtain c_a by determining the proportion of confirmed uncomplicated malaria treated with ACT obtained from the NMDR platform. The protective effectiveness of LLINs, denoted by u, is defined as $u = \epsilon_l \times c_l$, where ϵ_l represents the LLIN efficacy and c_l denotes the LLIN coverage (defined as access to and use of LLINs). The LLIN efficacy ϵ_l was assumed to be 0.90 for each of the six states. The 2015 LLIN coverage values c_l of 0.592, 0.559, 0.376, 0.563, 0.384, and 0.444 for Bauchi, Yobe, Kebbi, Zamfara,

Plateau, and Nasarawa, respectively, were obtained from [37]. Consequently, the corresponding values of u are 0.5328, 0.5031, 0.3384, 0.5067, 0.3456, and 0.3996 for Bauchi, Yobe, Kebbi, Zamfara, Plateau, and Nasarawa, respectively. The disease-induced death rate δ_h was obtained from [38] using 2015 as the baseline year. The malaria death rates across the six states are given as 7.58×10^{-5}, 6.22×10^{-5}, 1.27×10^{-4}, 8.24×10^{-5}, 7.57×10^{-5} and 8.24×10^{-5} per months for Bauchi, Yobe, Kebbi, Zamfara, Plateau, and Nasarawa respectively.

3.3 SMC-related parameters

SMC coverage rate ψ_t is computed from the SMC coverage data obtained from NMEP. The reported number of eligible children who received SMC often exceeds the estimated target population, making coverage levels exceeding 100%. Possible reasons for this include age-ineligible children inadvertently receiving SMC doses or underestimation of the target population size due to migration or internal displacement [39]. In order to avoid unrealistic coverage rates in the model, coverage was rescaled using the annual maximum number of children reached as the denominator and capped at 90%. SMC coverage rates where then calculated using $\psi_t = -\frac{\log_e(1-\Psi)}{\Delta t}$ where Ψ is the proportion of eligible children reached. ψ_t is described as a piecewise function and is given by:

$$\psi_t = \begin{cases} \psi_p, & \text{if } t \in \text{SMC campaign months} \\ 0, & \text{otherwise.} \end{cases} \tag{3.1}$$

where ψ_p is the SMC pulse rate. Figure 4 presents the computed SMC coverage rates by year of implementation and cycle.

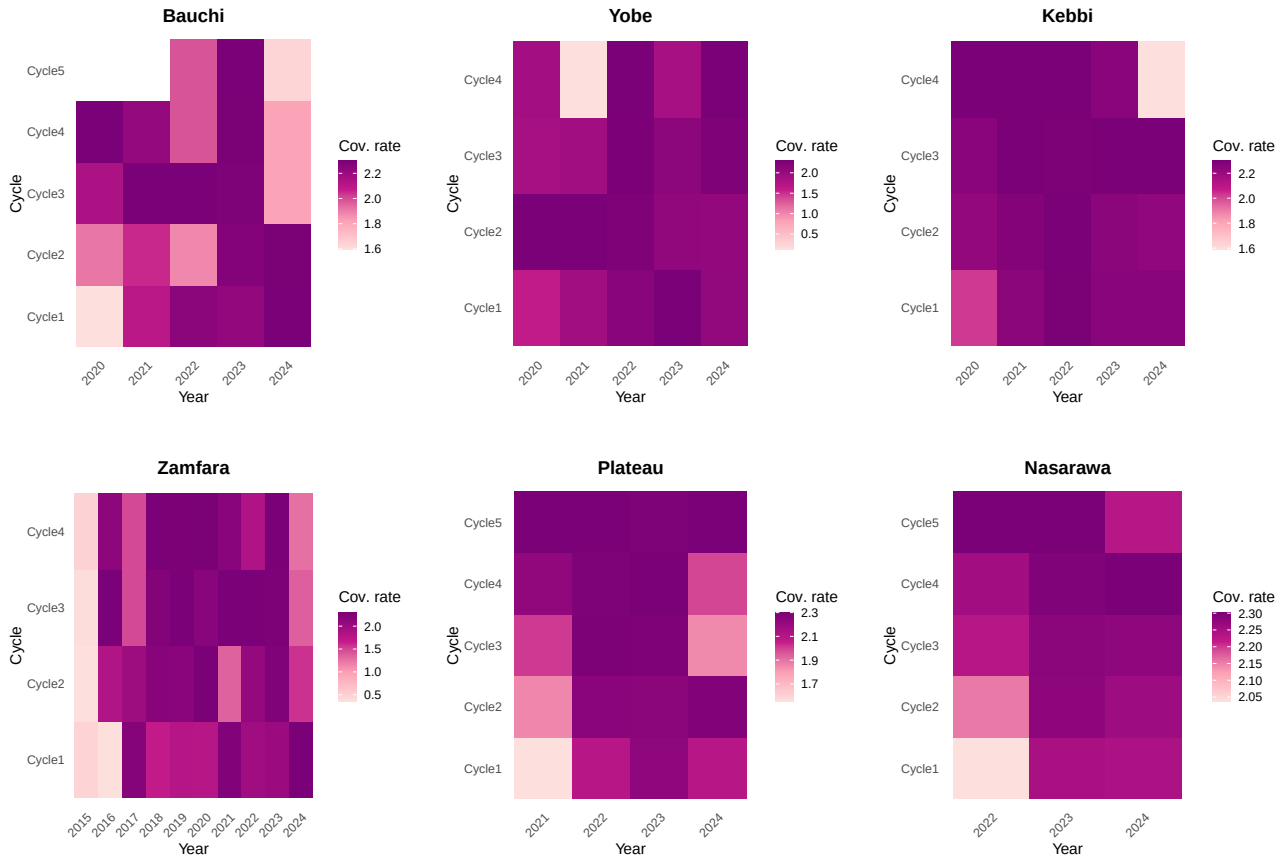


Figure 4: Heatmaps showing the computed SMC coverage rates by implementation cycle and year across the six study states. Each tile represents a specific SMC cycle within a given year, with colour intensity denoting the magnitude of the coverage rate

The protective effectiveness of SMC, $\tau = 0.75$ is obtained from the product of SMC's efficacy of 83.1%

[11] and SMC's coverage of 90%. The proportion of SMC-eligible children in the population, f is taken to be 20% [29].

Table 2: Fixed baseline parameter values of the model (2.12)

Parameter	Bauchi	Yobe	Kebbi	Zamfara	Plateau	Nasarawa	Range	**Dimension**	**Source**
Λ_h	10829.25	5246.08	6435.32	7123.69	6689.03	3592.37	-	Human/Month	Derived
Λ_v	39619194	18407298	26266620	28119816	24032436	14087730	-	Mosquitoes/Month	Derived
β_{vh}	0.1030	0.0387	0.0217	0.1086	0.0109	0.0386	0.010 - 0.27	1	[23]
β_{hv}	0.0554	0.0757	0.1027	0.0284	0.0407	0.1592	0.0072 - 0.64	1	[23]
τ	0.83	0.83	0.83	0.83	0.83	0.83	0.691 - 0.908	1	[23]
b_0	14	15	13	15	12	13	10 - 21	Month^{-1}	[34]
ρ_h	3	3	3	3	3	3	2 - 6	Month^{-1}	[34]
ρ_v	2.727	2.727	2.727	2.727	2.727	2.727	0.87 - 9.9	Month^{-1}	[34]
α	3.7190	2.6709	3.2845	2.1125	2.8146	3.3693	-	Month^{-1}	Derived
q	0.2	0.2	0.2	0.2	0.2	0.2	0.15 - 0.25	1	Assumed
μ_h	0.00164	0.00171	0.00147	0.00152	0.00167	0.00153	-	Month^{-1}	[29]
μ_v	2	2	2	2	2	2	1 - 3	Month^{-1}	[34]
δ_h	7.58×10^{-5}	6.22×10^{-5}	1.27×10^{-4}	8.24×10^{-5}	7.57×10^{-5}	8.24×10^{-5}	-	Month^{-1}	[38]
f	0.20	0.20	0.20	0.20	0.20	0.20	0.17 - 0.22	1	[29]
u	0.5328	0.5031	0.3384	0.5067	0.3456	0.3996	-	1	Derived

3.4 Initial conditions

To obtain the initial values of the model for each of the states, we take the total population in 2015 $N_h(0)$ to be 6,603,199, 3,067,883, 4,377,770, 4,686,636, 4,005,406, and 2,347,955 in Bauchi, Yobe, Kebbi, Zamfara, Plateau, and Nasarawa, respectively [29]. The initial symptomatic infectious human population $I_h(0)$ is taken to be the number of reported uncomplicated malaria cases across the states in January 2015. Thus, $I_h(0) = 20,328$ for Bauchi, 13,006 for Yobe, 177 for Kebbi, 9,204 for Zamfara, 577 for Plateau and 3,635 for Nasarawa. In line with studies suggesting that 73–98% of *P. falciparum* infections are asymptomatic [33], we assume that 80% of infections are asymptomatic and take $A_h(0) = 4I_h(0)$. The initial pre-infectious $E_h(0)$ is assumed to be $6I_h(0)$. Prior to the implementation of SMC in the states, the SMC-administered class is 0, so that $M_c(0) = 0$. Consequently, the initial number of susceptible humans is obtained as $S_h(0) = N_h(0) - (M_c(0) + E_h(0) + A_h(0) + I_h(0))$. Following the introduction of SMC, the SMC-administered compartment is initialized at the time of the first SMC cycle, denoted by t_c. Thus, $M_c(t_c)$ represents the number of children who received the first round of SMC treatment during the first implementation cycle in each state. These values are given as 666,418, 737,264, 1,109,571, 296,528, 754,951, and 838,800 for Bauchi, Yobe, Kebbi, Zamfara, Plateau, and Nasarawa, respectively.

Since there are no available data for the initial conditions of the vector population, we assume that the initial total population of female *Anopheles* mosquito is 3 times the total human population, that is, $N_v(0) = 3N_h(0) = 19,809,597$. The initial pre-infectious mosquito population is assumed to be $E_v(0) = 100,000$, while the initial infectious mosquito population is taken to be $I_v(0) = 500,000$ across the six states. Thus, the initial susceptible mosquito population is obtained as $S_v(0) = N_v(0) - (E_v(0) + I_v(0))$.

3.5 Model fitting and parameter estimation

To calibrate the model to the observed data of each of the states, we employ the nonlinear least squares method. The method is achieved by finding the set of parameters $\hat{\Theta} = (\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_k)$ that minimizes the sum of squared differences between the observed data $y_{t_i} = y_{t_i}, y_{t_i}, ..., y_{t_i}$ at time $t_i, i = 1, 2, ..., k$, and the corresponding model solution denoted by $h(t_i, \Theta)$ [40]. Thus, the objective function is given by

$$\hat{\Theta} = \operatorname{argmin} \sum_{i=1}^{k} \left[h(t_i, \Theta) - y_{t_i}\right]^2. \tag{3.2}$$

Consequently, the model solution $h(t_i, \hat{\Theta})$ provides the best fit to the observed data y_{t_i}. In order to quantify uncertainty in the estimated parameters and the corresponding model trajectories, we implement a parametric bootstrap procedure following [40].

Using the fitted model solution $h(t_i, \hat{\Theta})$, synthetic datasets are generated under an assumed observation error. Exploratory analysis of the incidence time series revealed substantial overdispersion, as the empirical variance exceeded the mean. Accordingly, the reported incidence is modeled using a negative binomial distribution with mean equal to the model-predicted incidence.

Specifically, for each time point t_i, let

$$\mu_i = h(t_i, \hat{\Theta})$$

denote the fitted incidence. For each bootstrap realization $s = 1, 2, \ldots, S$, a synthetic dataset $\{y_i^{*(s)}\}_{i=1}^{k}$ is generated according to

$$y_i^{*(s)} \sim \text{NegBin}(\mu_i, \kappa), \tag{3.3}$$

where κ is the dispersion parameter estimated from the empirical mean–variance relationship of the observed incidence data.

Each synthetic dataset is subsequently re-fitted using the nonlinear least squares procedure described above, yielding a new parameter estimate $\hat{\Theta}^{(s)}$. Repeating this process for 500 realizations produces the collection

$$\left\{\hat{\Theta}^{(1)}, \hat{\Theta}^{(2)}, \ldots, \hat{\Theta}^{(500)}\right\},$$

which provides an empirical approximation to the sampling distribution of the estimator.

Parameter uncertainty is quantified using the percentile method: for each parameter, the 95% confidence interval is obtained from the 2.5^{th} and 97.5^{th} empirical percentiles of its bootstrap distribution.

To propagate uncertainty to model outputs, each bootstrap parameter set $\hat{\Theta}^{(s)}$ is substituted into the transmission model to generate the corresponding epidemic trajectory $h(t, \hat{\Theta}^{(s)})$. The ensemble of trajectories obtained from all bootstrap realizations defines an empirical distribution of plausible epidemic dynamics. Pointwise 95% predictive intervals are constructed from the empirical quantiles of this ensemble at each time point, while the median trajectory is reported as the central estimate. Figure 5 shows the model calibration to monthly malaria cases from the six study states.

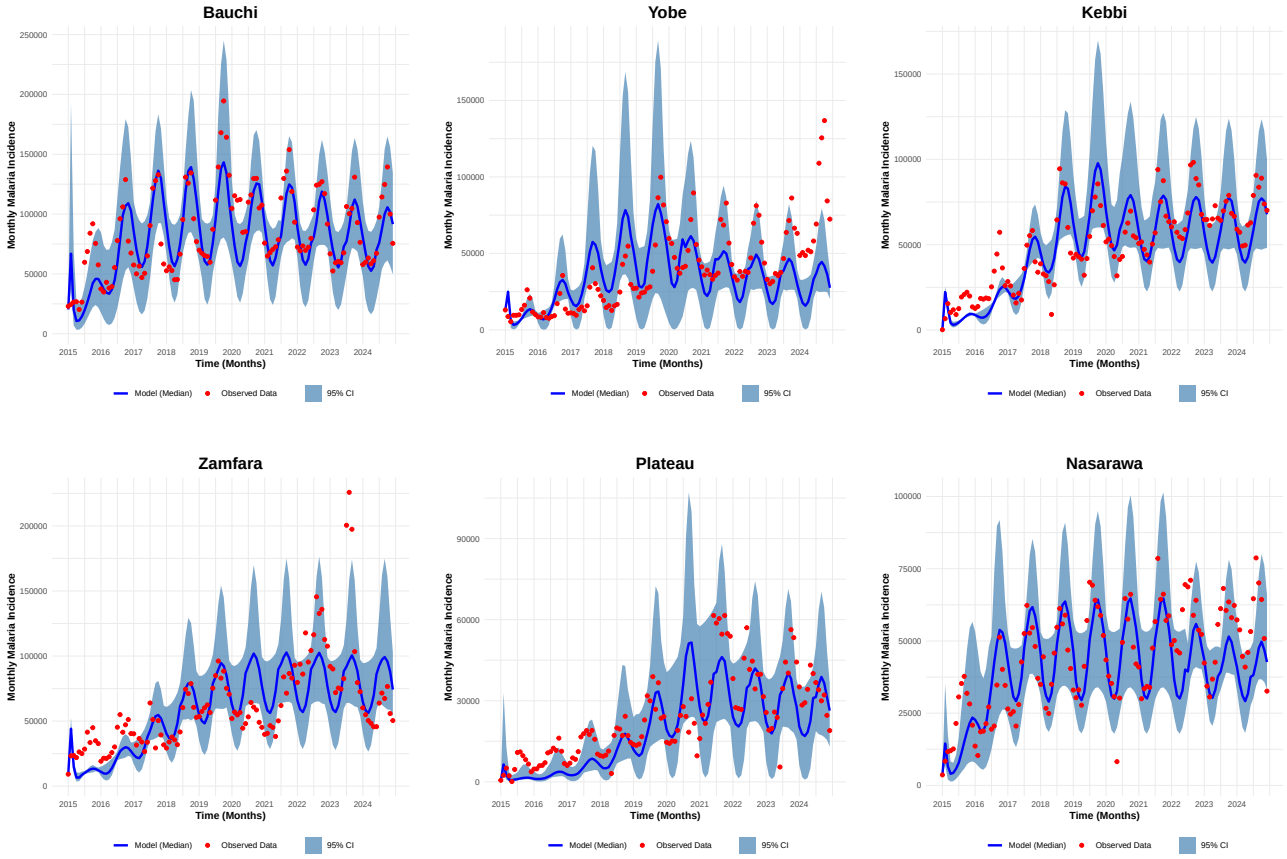


Figure 5: Model calibration to monthly malaria cases data in each of the six implementing states under consideration from January 2015 to December 2024. The red dots indicate the observed data while the blue line indicates the predicted model (median). The steelblue band represent the 95% CI.

4 Results

4.1 Quality of the model fit

Performance evaluation of model 2.12 was carried out using the Index of Agreement (Willmott's d), which measures the degree of model prediction error relative to the observed variability [41, 42]. Let

Table 3: Estimated modification parameter (σ), probability of asymptomatic individuals becoming symptomatic due to re-infection (γ) and amplitude (b_1) with 95% confidence interval

State	σ	γ	b_1
Bauchi	0.1567 (0.0010, 0.9900)	0.0954 (0.0703, 0.1641)	0.2467 (0.1768, 0.3189)
Yobe	0.3448 (0.1690, 0.5132)	0.2568 (0.1007, 0.8695)	0.3396 (0.2135, 0.4602)
Kebbi	0.0015 (0.0010, 0.2041)	0.1467 (0.0819, 0.4409)	0.1915 (0.1143, 0.2788)
Zamfara	0.4997 (0.2832, 0.5919)	0.4466 (0.1822, 0.6386)	0.2074 (0.0943, 0.3029)
Plateau	0.1131 (0.0613, 0.2226)	0.4274 (0.2709, 0.5425)	0.1861 (0.0402, 0.3152)
Nasarawa	0.4315 (0.1464, 0.6844)	0.0947 (0.0788, 0.2133)	0.2003 (0.1304, 0.2905)

Table 4: Estimated phase shift (ϕ) and waning rate of SMC treatment (η) with 95% confidence interval

State	ϕ	η
Bauchi	7.9193 (7.5501, 8.2952)	1.0696 (0.0985, 1.0700)
Yobe	8.2655 (7.7397, 8.7958)	0.1470 (0.0145, 0.5000)
Kebbi	7.9607 (7.3969, 8.5883	0.0962 (0.0010, 0.5000)
Zamfara	7.4623 (6.7170, 8.0886)	0.0977 (0.0100, 0.6381)
Plateau	6.9612 (6.2429, 7.6211)	0.1206 (0.0100, 0.4471)
Nasarawa	7.2328 (6.6621, 7.9150)	0.9513 (0.1596, 1.0700)

y_i denote the reported uncomplicated malaria cases, $\hat{y}_i$ the model's predicted cases, and $\bar{y}$ denoting the mean of y_i. The Index of Agreement d is defined as:

$$d = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(|\hat{y}_i - \bar{y}| + |y_i - \bar{y}|\right)^2}. \tag{4.1}$$

The value of d ranges between 0 and 1, where $d = 1$ indicates perfect agreement between model predictions and observed data, while $d = 0$ indicates no agreement between the model and observed data. The Index of Agreement, d was computed for each of the six states to assess the goodness-of-fit of the model. Table 5 presents the Index of Agreement d with $d > 0.75$ across all states suggesting strong degree of agreement between the data and the model.

Table 5: Index of Agreement for Selected States

State	Index of Agreement (d)
Bauchi	0.8231
Yobe	0.7625
Kebbi	0.9151
Zamfara	0.7938
Plateau	0.8850
Nasarawa	0.8351

Furthermore, the quality of the model fit to the data was assessed by analyzing the temporal variation of the residuals as a function of time. The residuals, defined as the difference between the best fit of the model and the observed data is expressed mathematically as [40]:

$$\text{res}(t_i) = h(t_i, \hat{\Theta}) - y_{t_i}, \tag{4.2}$$

where $h(t_i, \hat{\Theta})$ is the model prediction and y_{t_i} is the observed data at time t_i. Figure 6 shows the temporal variation of residuals as a function of time. The random patterns of the residuals across the six states confirms that the model offers a reasonably good fit.

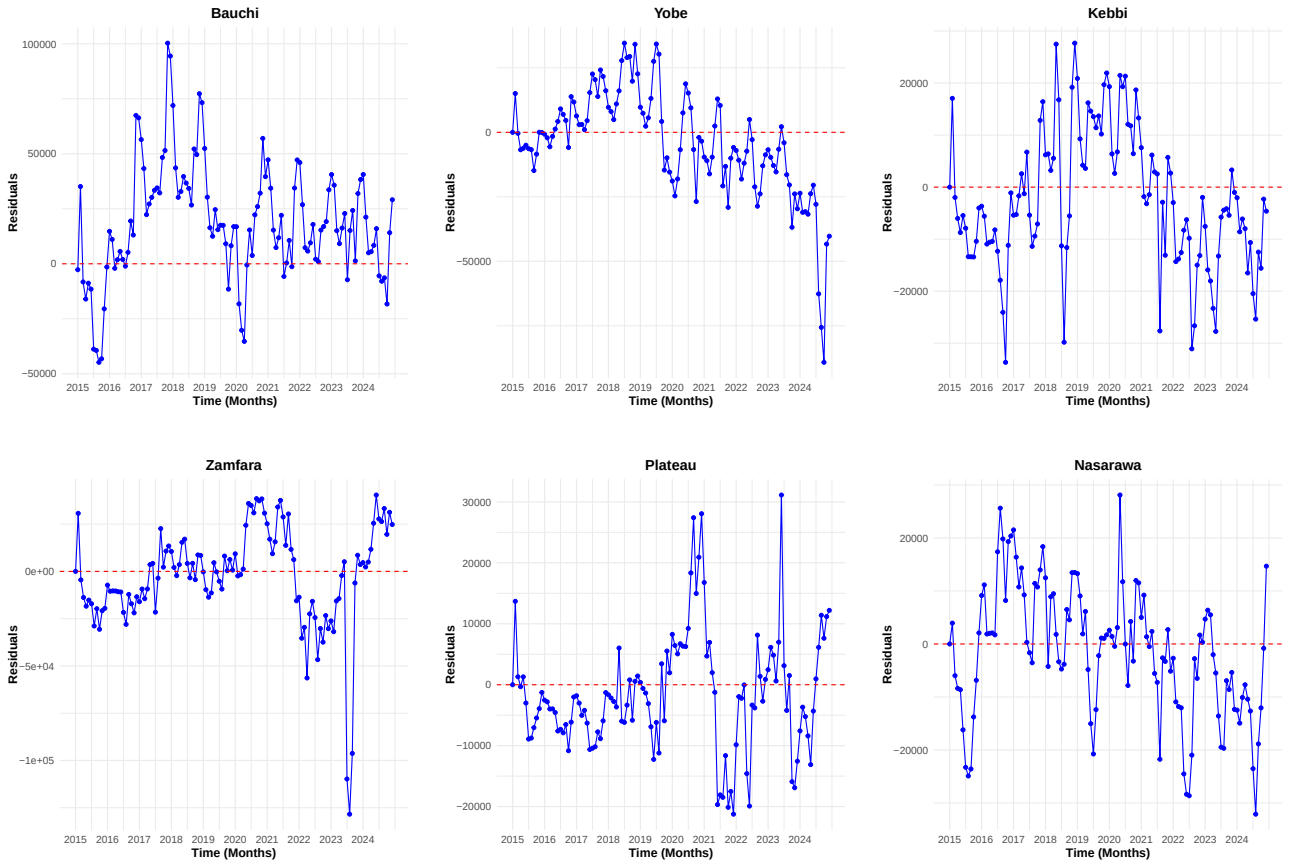


Figure 6: Temporal variation of residuals as a function of time with the random pattern of the residuals suggesting that the model offers a good fit

4.2 Estimation of malaria cases averted due to SMC

The impact of SMC was assessed from the commencement of implementation in each of the six study states by comparing model outcomes with a counterfactual scenario in which SMC was not implemented over the same time period. Figure 7 presents the scenario analysis of simulated malaria incidence across the six implementing states under two scenarios - without SMC (No SMC) and with SMC implementation. For Bauchi State, SMC was estimated to avert 1,077, 911 cases (95% CI: 572,225 – 1,534,358), corresponding to 18.0% reduction (95% CI: 10.3 – 24.3%) in malaria incidence between 2020 and 2024. For Yobe State, SMC was estimated to avert 804,712 cases (95% CI: 587,809 – 1,273,920), corresponding to 26.9 % reduction (95% CI: 23.6 – 39.8%) in malaria incidence between 2020 and 2024. An estimated 1,021,874 malaria cases (95% CI: 741,370 – 1,318,286) were averted in Kebbi State, corresponding to a 23.9% reduction (95% CI: 19.5 – 26.9%) in malaria incidence between 2020 and 2024. Between 2015 and 2024 when SMC was implemented in Zamfara State, an estimated 2,258,356 cases (95% CI: 1,205,684 – 3,794,694) was averted, corresponding to 24.1% reduction (95% CI: 14.3 – 37.1%) in malaria incidence in the state. For Plateau State, SMC was estimated to avert 377,733 cases (95% CI: 132,061 – 752,552), corresponding to 21.1% reduction (95% CI: 12.1 – 28.0%) in malaria incidence between 2021 and 2024. Lastly, for Nasarawa State, SMC was estimated to avert 232,597 cases (95% CI: 156,162 – 343,903), corresponding to 14.5% reduction (95% CI: 9.6 – 20.7%) in malaria incidence between 2022 and 2024. These results are clearly presented in Table 6.

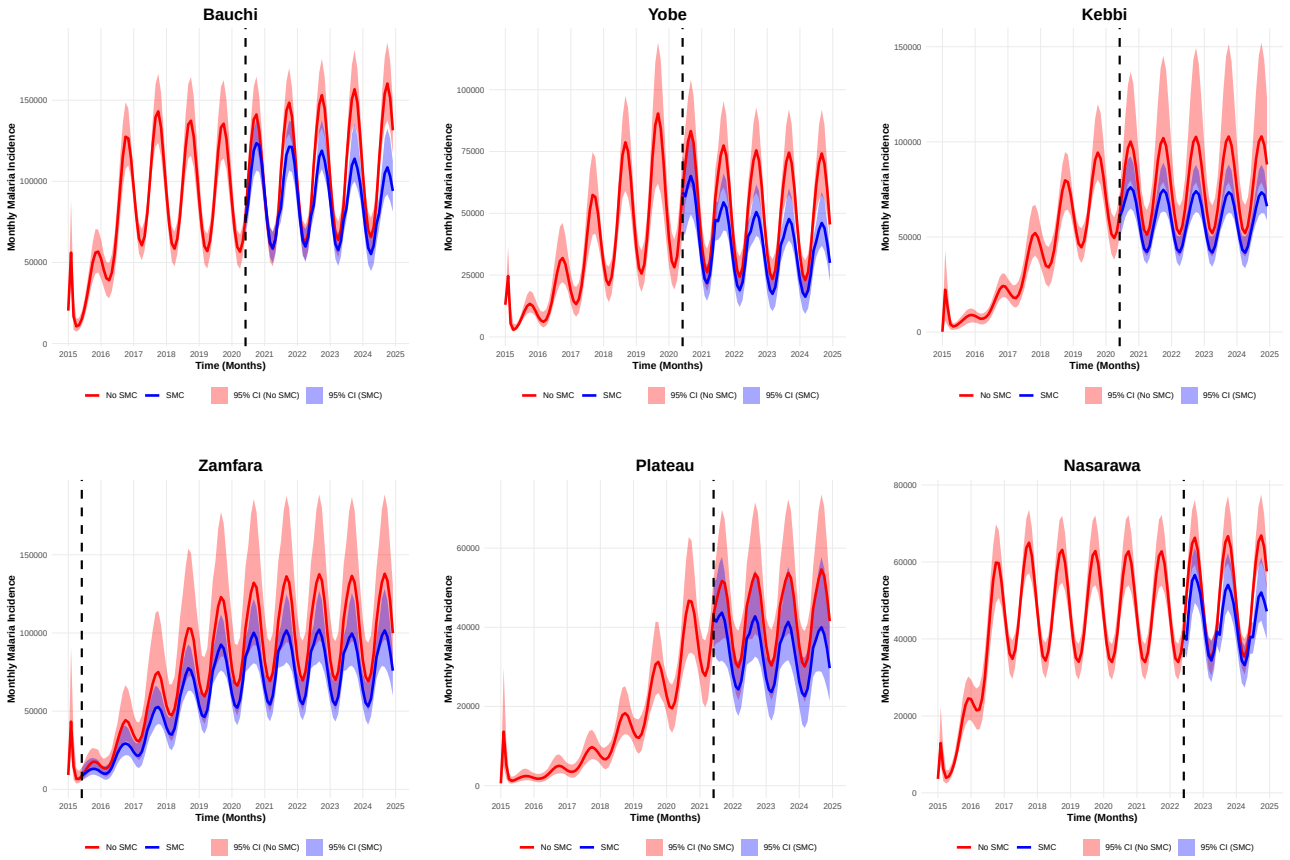


Figure 7: Simulated malaria incidence in the six implementing states under two scenarios: without SMC (No SMC) and with SMC implementation. The red lines represent the model-predicted incidence in the absence of SMC while the blue lines represent the model-predicted incidence with SMC implementation. The black dashed lines indicate the commencement of SMC implementation in each state. The shaded regions denote the corresponding 95% confidence intervals.

4.3 Global sensitivity analysis

In order to quantify how the dynamics of malaria transmission and prevalence in each of the six study states is being influenced by model parameters, we carry out a global sensitivity analysis (GSA). GSA is used to assess how uncertainty in model input parameters influences variability in model outcomes within a specified parameter space [43, 44, 45]. The method gives insights into which parameter exerts the greatest influence on model outcomes and helps to identify key drivers of malaria prevalence in order to guide and prioritise malaria intervention strategies [45]. In this study, GSA was performed using the Latin Hypercube Sampling (LHS) method in combination with Partial Rank Correlation Coefficient (PRCC).

Following the framework used in [44], plausible ranges for each of the model parameters were defined by allowing a variation of ±33% around their baseline values with the assumption that each of the parameter follows a uniform probability distribution. The LHS, a stratified Monte Carlo sampling method [43] was used to divide each of the parameter's range into 1000 equal sub-intervals and randomly draws a single sample from each sub-interval. The model output considered was the average number of symptomatic infectious humans (I_h) during the post-SMC implementation period, representing the mean malaria prevalence post-SMC implementation period. The sensitivity of malaria prevalence to each model parameter was then quantified using PRCC. The PRCC index measures the relative influence of the parameters on the model output and also indicates the direction of their relationship [43]. PRCC values range from -1 to +1, with values closer to ±1 indicating that the parameter has a strong influence on the model output [43].

Table 6: Estimated malaria cases averted and percentage reduction in incidence due to SMC across study states.

State	Implementation period	Cases averted (95% CI)	% Reduction (95% CI)
Bauchi	2020 - 2024	1,077,911 (572.225, 1,534,358)	18.0 (10.3 - 24.3)
Yobe	2020 - 2024	804,712 (587,809, 1,273,920)	26.9 (23.6 - 39.8)
Kebbi	2020 - 2024	1,021,874 (741,370, 1,318,286)	23.9 (19.5 - 26.9)
Zamfara	2015 - 2024	2,258,356 (1,205,684, 3,794,694)	24.1 (14.3 - 37.1)
Plateau	2021 - 2024	377,733 (132,061 - 752,552)	21.1 (12.1 - 28.0)
Nasarawa	2022 - 2024	232,597 (156,162 - 343,903)	14.5 (9.6 - 20.7)

GSA identified the set of parameters that strongly influence malaria prevalence during the post-SMC implementation period. Across all six states, the baseline mosquito biting rate b_0 is shown to have the strongest positive influence on malaria prevalence, with PRCC values ranging from 0.8956 in Bauchi to 0.9237 in Plateau. Similarly, the mosquito recruitment rate Λ_v and the transmission probabilities β_{vh} and β_{hv} exhibit strong positive correlations with the model output..

On the other hand, the natural death rate of mosquitoes μ_v shows a strong negative correlation with the model output across all states with absolute PRCC values ranging between 0.9263 in Bauchi and 0.9458 in Plateau indicating that higher mosquito mortality reduces malaria transmission substantially. The effectiveness of LLINs u and the recovery rate of symptomatic humans due to treatment α also exhibit strong negative correlations. Parameters such as ρ_v and q show moderate positive correlations while the remaining parameters show relatively low PRCC values and therefore have weak influence on the model output. To visualise the influence of each model parameters on malaria prevalence across the six study states, tornado plots are shown in Figure 8.

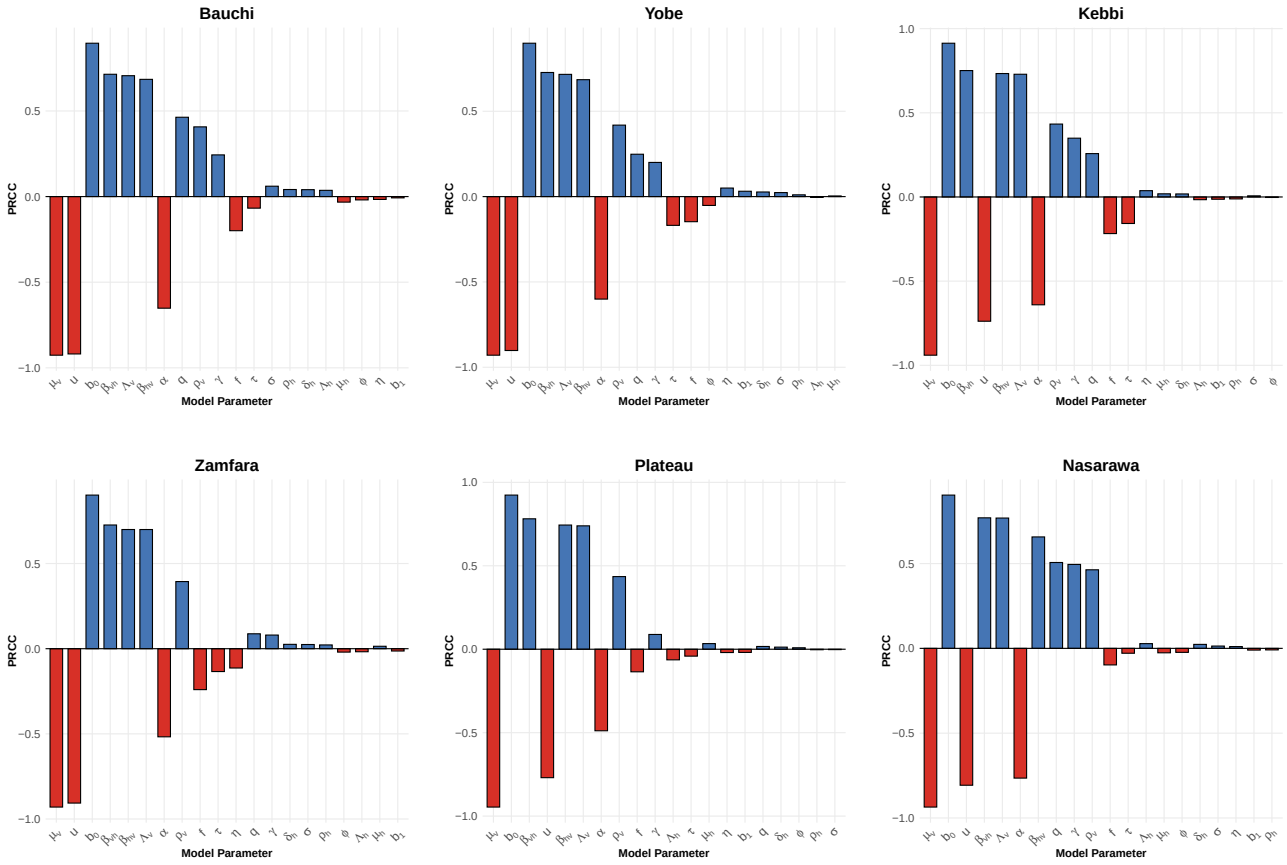


Figure 8: Tornado plots showing the sensitivity of malaria prevalence to model parameters across the six study states.

Furthermore, we evaluate the combined effects of SMC coverage ψ_t and the two most sensitive model parameters - the (baseline) mosquito biting rate (b_0) and the mosquito natural mortality rate (μ_v) on total malaria incidence during the post-SMC implementation period. The incidence heatmaps in Figure 9 and Figure 10 use a colour gradient to represent total malaria cases. Blue denotes lower incidence while yellow indicates higher incidence.

Figure 9 shows the mosquito biting rate and SMC coverage interaction across the six study states. At low biting rates (between 5 to 10 bites per month), increasing SMC coverage results in a significant decline in total malaria cases in all the states. At very high mosquito biting rate, i.e 20 - 25 bites per month, the heatmaps indicate persistently high incidence even at higher SMC coverage rates. Figure 10 presents the combined effect of mosquito natural mortality μ_v rate and SMC coverage rate ψ_t on total malaria incidence across the study states. As μ_v increases from 1.5 to 5 per months, the colour gradient changes from yellow to deep blue, indicating a substantial decline in total malaria cases. At very low mortality rate (longer mosquito lifespan), malaria incidence remains very high even at higher SMC coverage levels.

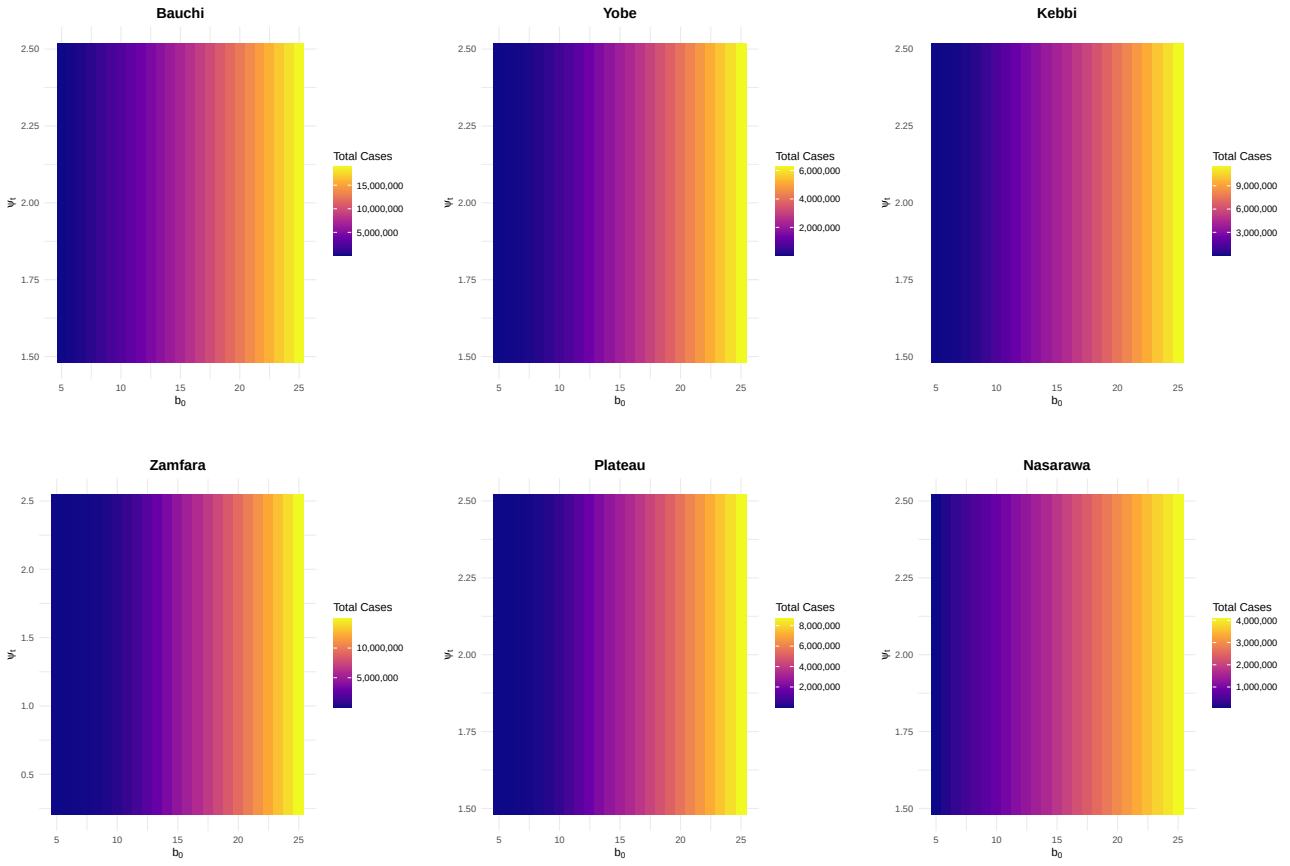


Figure 9: Variation in total malaria cases as a function of SMC coverage rate ψ_t and mosquito biting rate b_0.

5 Discussion

Results from our modelling study revealed that the implementation of SMC across all six study states led to a consistent reduction in malaria incidence, although the magnitude of impact differed from state to state. Overall, reductions in malaria morbidity ranged from approximately 15% to 27%, indicating that SMC has had a significant population-level public health impact in Nigeria.

The largest reduction due to SMC was seen in Yobe State (26.9%), followed by Zamfara, Kebbi and Plateau States, where the incidence of malaria decreased by more than 20%. In contrast, Bauchi and Nasarawa States showed relatively smaller reductions (14.5 - 18.0%). In absolute terms, the total

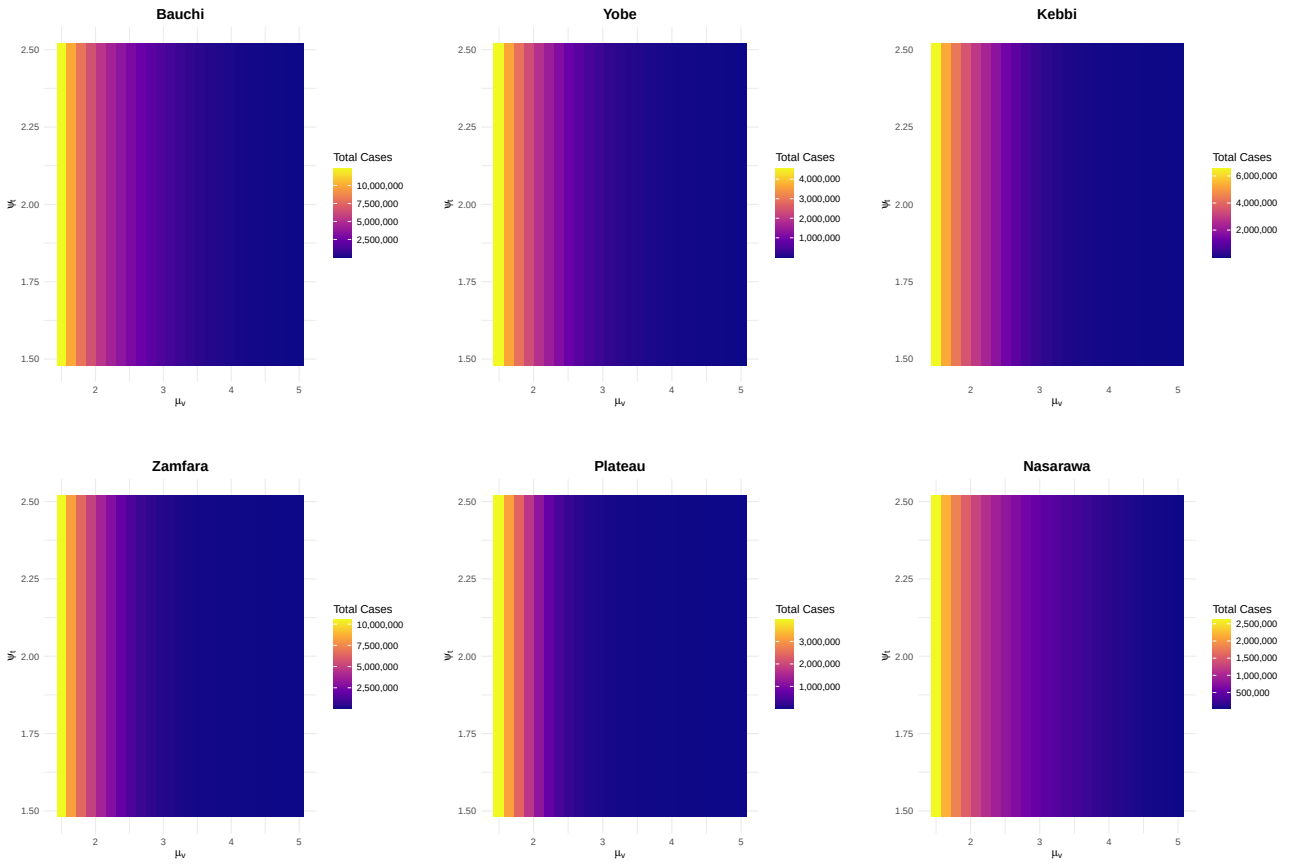


Figure 10: Variation in total malaria cases as a function of SMC coverage rate ψ_t and mosquito natural mortality rate μ_v.

number of cases averted was quite substantial, especially in Zamfara State where over two million cases were averted and Kebbi State, where over one million cases were averted.

These differences in magnitude of impact may reflect variations in transmission intensity, seasonality, implementation timing, or operational coverage across the states. In particular, earlier introduction of SMC in some states may have contributed to greater cumulative reductions in malaria burden over time. These findings highlight the population-level impact of sustained SMC implementation and are consistent with previous studies [25, 26] demonstrating the effectiveness of SMC in reducing malaria burden in states with seasonal transmission in Nigeria, and underscore the importance of continued scale-up and optimization of SMC in Nigeria.

The results of the global sensitivity analysis highlights key public health implications for the prevention and control of malaria in each of the six study states. The analysis reveals that malaria transmission dynamics in the study states are strongly driven by parameters associated with the vector population and transmission processes. In particular, b_0, the baseline mosquito biting rate is shown to exert the greatest influence on malaria burden across all states. This highlights the critical role of vector-human contact in sustaining malaria transmission and suggests that interventions that limits mosquito biting rates, such as LLINs and other vector control strategies, can significantly reduce malaria burden. The mosquito recruitment rate Λ_v and the transmission probabilities β_{vh} and β_{hv} also showed strong positive correlations with malaria prevalence. These parameters determine the rate at which mosquitoes are being recruited into the population and the efficiency with which the parasite is transmitted between humans and mosquitoes. This strong influence emphasizes the importance of vector control and environmental management measures geared at reducing mosquito breeding sites.

The strong negative correlation exhibited by u_v, the natural mortality rate of mosquito and the model output across all states implies that increasing mosquito mortality can reduce malaria transmission substantially, further supporting the need for scale-up of vector control interventions such as LLINs.

The effectiveness of LLINs and the recovery rate of symptomatic humans due to treatment were also negatively associated with malaria prevalence. This highlights the significance of both malaria preventive measures and effective case management in reducing malaria transmission.

These findings suggest that malaria control interventions targeting mosquito biting behaviour, mosquito population size, and transmission probability are likely to have the greatest impact on reducing malaria burden in the study states.

The study is however not without some limitations. Firstly, the confirmed uncomplicated malaria cases data used in the study are mostly from public health institutions, and may not reflect the accurate malaria incidence in the states under consideration. As a result, cases managed in private institutions and pharmaceutical stores may not be reported, potentially leading to an underestimation of the total disease burden and, consequently, the impact of SMC. Secondly, the SMC coverage data used in this study indicated that, in some cycles, the number of children reported to have received SMC exceeded the estimated target population, resulting in coverage values greater than 100%. To address this, coverage levels were capped at 90%. While this adjustment seemed reasonable, it does not accurately reflect the true coverage levels for eligible children. Consequently, this may lead to either underestimation or overestimation of the true impact of SMC.

Also, the model did not incorporate climatic factors such as rainfall and temperature which are known to influence seasonal malaria transmission. This may limit the ability of the model in capturing the seasonal and climatic variability in transmission, which could affect the accurate estimation of SMC's impact. Incorporating climatic factors in future studies may improve the accuracy of the model and provide a more comprehensive assessment of SMC's effects.

Despite these limitations, the study provides policymakers with useful insights into the population-level impact and effectiveness of SMC in Nigeria. It offers data-driven roadmap for integrating SMC with other vector control interventions.

6 Conclusion

A deterministic compartmental model was developed to assess the effects of seasonal malaria chemoprevention (SMC) on malaria incidence in six implementing states in Nigeria. The findings show that SMC is highly effective and has substantially reduced millions of malaria cases in Nigeria. These results provide evidence-based support for the continued implementation and scale-up of SMC in states with highly seasonal transmission, as it offers both direct protective effects among eligible children and indirect population-level benefits across the wider community. Therefore, sustained investment in SMC implementation and strengthened program delivery systems are essential to preserve and extend these gains.

In addition, The findings in this study also provide important context for SMC implementation. The effectiveness of SMC programs in preventing malaria in Nigeria can be greatly enhanced when combined with vector control interventions, including improved LLIN coverage and usage, and larva source management. Integrating SMC with sustained vector control and effective case management is therefore essential for achieving significant reductions in malaria burden in the study states.

In conclusion, this study provides evidence to guide public health policy in Nigeria, emphasizing that sustained reductions in malaria incidence requires coordinated investment in integrated interventions that combine SMC and vector control measures.

Abbreviations

SMC	Seasonal Malaria Chemoprevention
WHO	World Health Organization
NMEP	National Malaria Elimination Program

LLINs	Long-Lasting Insecticides Nets
ACT	Artemisinin-based Combination Therapy
IRS	Indoor Residual Spray
GSA	Global Sensitivity Analysis
TEG	Technical Expert Group
SPAQ	Sulfadoxine-Pyrimethamine plus Amodiaquine
PfPR	Plasmodium falciparum parasite rate
CDDs	Community Drug Distributors
CI	Confidence Interval

Declarations

Ethics approval and consent to participate

This study involved the secondary analysis of fully anonymized, aggregate surveillance data obtained from the Nigerian National Malaria Data Repository. Ethical review and approval were waived for this study as it did not involve direct interaction with human subjects or access to identifiable personal information.

Consent for publication

Not applicable

Availability of data and materials

The monthly reported malaria cases data were obtained from the National Malaria Data Repository (NMDR - https://nmdrnigeria.ng/dhis-webcommons/security/login.action) owned by NMEP. The data are not publicly available but are however available from the corresponding author upon reasonable request and with permission of NMEP.

Competing interests

The authors declare that they have no competing interests.

Funding

This study was funded by a grant from the BMGF (INV-047051). The funders had no role or influence on the design and interpretation of the data collected, as well as in writing the manuscript.

Authors' contributions

OAM: Conceptualization, writing - original draft, methodology, writing - review and editing, formal analysis
EAB: Conceptualization, methodology, writing - review and editing, supervision, funding acquisition, resources, project administration
OO: Conceptualization, resources, data curation
LSA: Methodology, supervision, project administration
AA: Software, formal analysis, writing - review and editing

IIO: Software, formal analysis, writing - review and editing
SAO: Software, formal analysis, writing - review and editing
AON: Software, formal analysis, writing - review and editing
DOO: Software, formal analysis, writing - review and editing
NE: Resources, data curation
All authors reviewed the manuscript.

Acknowledgement

The authors wish to express their sincere appreciation to the National Malaria Elimination Programme (NMEP) for providing the data used in this study. The authors also wish to express their gratitude to the anonymous reviewers for their useful suggestions and comments.

References

[1] Centers for Disease Control and Prevention. Dpdx – laboratory identification of parasites of public health concern: Malaria. https://www.cdc.gov/dpdx/malaria/index.html, 2025. Accessed: 2025-10-28.

[2] World Health Organization. Stakeholders take on malaria, top killer disease with innovative tools, 2023. https://www.afro.who.int/countries/nigeria/news/stakeholders-take-malaria-top-killer-disease-innovative-tools.

[3] World Health Organization. Weekly epidemiological record, 10 may 2024. *Weekly Epidemiological Record*, 99(19):225–248, 2024.

[4] Palang Chotsiri, Nicholas J White, and Joel Tarning. Pharmacokinetic considerations in seasonal malaria chemoprevention. *Trends in Parasitology*, 38(8):673–682, 2022.

[5] World Health Organization. Guidelines for malaria, 2022.

[6] Severe Malaria Observatory. Malaria facts: Nigeria, 2023. https://www.severemalaria.org/countries/nigeria.

[7] National Malaria Elimination Programme. National malaria strategic plan 2021–2025, 2021.

[8] World Health Organization. *Seasonal Malaria Chemoprevention with Sulfadoxine–Pyrimethamine Plus Amodiaquine in Children: A Field Guide*. World Health Organization, Geneva, Switzerland, 2 edition, 2023.

[9] SMC Alliance. Smc alliance: Nigeria, 2023. https://www.smc-alliance.org/nigeria.

[10] Thomas Druetz. Evaluation of direct and indirect effects of seasonal malaria chemoprevention in mali. *Scientific Reports*, 8(1):8104, 2018.

[11] Nnenna Ogbulafor, Perpetua Uhomoibhi, Emmanuel Shekarau, Jamilu Nikau, Chukwu Okoronkwo, Nadia ML Fanou, Ibrahima Marietou Mbaye, Jean-Louis Ndiaye, Andre-Marie Tchouatieu, Abena Poku-Awuku, et al. Facilitators and barriers to seasonal malaria chemoprevention (smc) uptake in nigeria: a qualitative approach. *Malaria journal*, 22(1):120, 2023.

[12] Malaria Consortium. Seasonal malaria chemoprevention: New geographies in nigeria and quality of delivery, 2022. https://www.malariaconsortium.org/resources/publications/archive.

[13] Matthew Milligan, M. Kana, S. Lal, and P. Snell. Seasonal malaria chemoprevention in nigeria: Coverage surveys 2017, 2018.

[14] Kabiru Abubakar Gulma. Exploratory study of seasonal malaria chemoprevention in kebbi state. *Indian Journal of Public Health*, 67(3):352–356, 2023.

[15] Malaria Consortium. Smc program: Philanthropy report 2023, 2024.

[16] Seyed M Moghadas. Gaining insights into human viral diseases through mathematics. *European Journal of Epidemiology*, 21:337–342, 2006.

[17] Sandip Mandal, Ram Rup Sarkar, and Somdatta Sinha. Mathematical models of malaria: A review. *Malaria Journal*, 10:1–19, 2011.

[18] OC Collins and KJ Duffy. Mathematical model for malaria dynamics in nigeria. *Infectious Disease Modelling*, 7(4):728–741, 2022.

[19] Ifeoma D Ozodiegwu, Monique Ambrose, Beatriz Galatas, Manuela Runge, Aadrita Nandi, Kamaldeen Okuneye, Neena Parveen Dhanoa, Ibrahim Maikore, Perpetua Uhomoibhi, Caitlin Bever, et al. Application of mathematical modelling to inform national malaria intervention planning in nigeria. *Malaria journal*, 22(1):137, 2023.

[20] Emmanuel A Bakare, Idowu I Olasupo, Micheal Imoudu, Afeez Abidemi, Deborah O Daniel, Samuel A Osikoya, Oluwaseun A Mogbojuri, Aaron O Nwana, Dolapo O Oniyelu, Ronke D Olorunfemi, et al. Modelling the effect of long-lasting insecticidal nets on malaria transmission dynamics in kebbi state, nigeria. *Infectious Disease Modelling*, 2026.

[21] EA Bakare, BO Onasanya, S Hoskova-Mayerova, and O Olubosede. Analysis of control interventions against malaria in communities with limited resources. *Analele ştiinţifice ale Universităţii" Ovidius" Constanţa. Seria Matematică*, 29(2):71–91, 2021.

[22] Ifeanyi Sunday Onah. Seasonal dynamics and control of malaria. *Nonlinear Analysis: Real World Applications*, 91:104584, 2026.

[23] Matthew Cairns, Serign Jawo Ceesay, Issaka Sagara, Issaka Zongo, Hamit Kessely, Kadidja Gamougam, Abdoulaye Diallo, Johnbull Sonny Ogboi, Diego Moroso, Suzanne Van Hulle, et al. Effectiveness of seasonal malaria chemoprevention (smc) treatments when smc is implemented at scale: case–control studies in 5 countries. *PLoS medicine*, 18(9):e1003727, 2021.

[24] Ebenezer Baba, Prudence Hamade, Harriet Kivumbi, Maddy Marasciulo, Kolawole Maxwell, Diego Moroso, Arantxa Roca-Feltrer, Adama Sanogo, Joanna Stenstrom Johansson, James Tibenderana, et al. Effectiveness of seasonal malaria chemoprevention at scale in west and central africa: an observational study. *The Lancet*, 396(10265):1829–1840, 2020.

[25] Monica Anna de Cola, Benoît Sawadogo, Sol Richardson, Taiwo Ibinaiye, Adama Traoré, Cheick Saïd Compaoré, Chibuzo Oguoma, Olusola Oresanya, Gauthier Tougri, Christian Rassi, et al. Impact of seasonal malaria chemoprevention on prevalence of malaria infection in malaria indicator surveys in burkina faso and nigeria. *BMJ global health*, 7(5), 2022.

[26] Ebenezer C Ikechukwu, Ekechi Okereke, Olabisi Ogunmola, Jennifer Chukwumerije, Daniel Emeto, Emmanuel Salifu, Ayodeji Balogun, Chibuzo Oguoma, Emmanuel Shekarau, Nnenna Ogbulafor, et al. Impact of seasonal malaria chemoprevention: a plausibility evaluation of routine data from health facilities in three implementing states in nigeria. *Malaria Journal*, 24(1):1–12, 2025.

[27] Sikai Huang, Kevin Baker, Taiwo Ibinaiye, Olusola Oresanya, Chuks Nnaji, and Sol Richardson. Impact of seasonal malaria chemoprevention based on the number of medicines doses received on malaria burden among children aged 3–59 months in nigeria: A propensity score-matched analysis. *Tropical Medicine & International Health*, 29(8):668–679, 2024.

[28] World Health Organization. Report on malaria in nigeria. *Report on malaria in Nigeria*, 2022. https://www.afro.who.int/countries/nigeria/publication/report-malaria-nigeria-2022.

[29] National Population Commission (Nigeria). Nigeria population projections and demographic indicators. Technical report, NPC, Abuja, Nigeria, 2020.

[30] Taiwo Ibinaiye, Kunle Rotimi, Ayodeji Balogun, Adaeze Aidenagbon, Chibuzo Oguoma, Kevin Baker, Olabisi Ogunmola, Olusola Oresanya, Christian Rassi, and Chuks Nnaji. Urban–rural differences in seasonal malaria chemoprevention coverage and characteristics of target populations in nine states of nigeria: a comparative cross-sectional study. *Malaria Journal*, 23(1):4, 2024.

[31] Olusola Oresanya and Adaeze Aidenagbon. Smc: New geographies in nigeria. In *ASTMH Annual Meeting*, 2022.

[32] Dolie D Laishram, Patrick L Sutton, Nutan Nanda, Vijay L Sharma, Ranbir C Sobti, Jane M Carlton, and Hema Joshi. The complexities of malaria disease manifestations with a focus on asymptomatic malaria. *Malaria journal*, 11(1):29, 2012.

[33] Kim A Lindblade, Laura Steinhardt, Aaron Samuels, S Patrick Kachur, and Laurence Slutsker. The silent threat: asymptomatic parasitemia and malaria transmission. *Expert review of anti-infective therapy*, 11(6):623–639, 2013.

[34] Nakul Chitnis, James M Hyman, and Jim M Cushing. Determining important parameters in the spread of malaria through the sensitivity analysis of a mathematical model. *Bulletin of mathematical biology*, 70(5):1272–1296, 2008.

[35] Kolapo M Oyebola, Funmilayo C Ligali, Afolabi J Owoloye, Oluwagbemiga O Aina, Yetunde M Alo, Blessing Erinwusi, Michael J Olufemi, and Babatunde L Salako. Assessing the therapeutic efficacy of artemether-lumefantrine for uncomplicated malaria in lagos, nigeria: a comprehensive study on treatment response and resistance markers. *Malaria journal*, 23(1):261, 2024.

[36] Joy C Ebenebe, Godwin Ntadom, Jose Ambe, Robinson Wammanda, Nma Jiya, Finomo Finomo, George Emechebe, Olugbenga Mokuolu, Kazeem Akano, Chimere Agomo, et al. Efficacy of artemisinin-based combination treatments of uncomplicated falciparum malaria in under-five-year-old nigerian children ten years following adoption as first-line antimalarials. *The American journal of tropical medicine and hygiene*, 99(3):649, 2018.

[37] Nigeria Malaria Indicator Survey. Nigeria mis 2015, 2015. https://dhsprogram.com/pubs/pdf/MIS20/MIS20.pdf.

[38] Malaria Atlas Project. Malaria incidence rate data explorer, 2022. https://data.malariaatlas.org.

[39] Malaria Consortium. Quantitative report on smc 2020, 2021.

[40] Gerardo Chowell. Fitting dynamic epidemic models. *Infectious Disease Modelling*, 2(3):379–398, 2017.

[41] Cort J. Willmott. On the validation of models. *Physical Geography*, 2(2):184–194, 1981.

[42] David R Legates and Gregory J McCabe. Evaluating goodness-of-fit measures. *Water Resources Research*, 35(1):233–241, 1999.

[43] Jianyong Wu, Radhika Dhingra, Manoj Gambhir, and Justin V Remais. Sensitivity analysis of infectious disease models: methods, advances and their application. *Journal of The Royal Society Interface*, 10(86), 2013.

[44] Calistus N Ngonghala, Sara Y Del Valle, Ruijun Zhao, and Jemal Mohammed-Awel. Quantifying the impact of decay in bed-net efficacy on malaria transmission. *Journal of theoretical biology*, 363:247–261, 2014.

[45] Hemaho B Taboe, Megan Sin, Afsana Yesmin, Eric Van Amber, Olivia Prosper Feldman, Ruijun Zhao, and Calistus N Ngonghala. Unmasking asymptomatic malaria: The role of acquired immunity and integrated interventions in sustained transmission control. *Applied Mathematical Modelling*, page 116636, 2025.