MODELING MALARIA TRANSMISSION TO OPTIMIZE TREATMENT AND CONTROL STRATEGIES IN RIVERS STATE, NIGERIA

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Abstract

Nigeria accounts for 31.3% of global malaria deaths and 26.6% of cases, with low insecticide-treated net (ITN) coverage, limited artemisinin-based combination therapy (ACT) use due to financial barriers, and poor preventive chemotherapy uptake. Rivers State, with its high burden and intervention gaps, is ideal for evaluating transmission dynamics and control.

This study developed a deterministic compartmental model comprises of humans: Susceptible, Infected, Treated, Recovered (SITR) and vectors: Susceptible, Infected (SI), using parameters from national reports and literature. Ordinary differential equations assessed intervention impacts via sensitivity and scenario analyses on the basic (R_0) and effective (R_e) reproduction number.

Under the current coverage(10% ACT treatment, 15% ITN coverage, 32% IPTp-SP uptake) R_e was estimated at1.90. Further scenario analysis showed that increasing ITN and ACT treatment coverage to 40% reduced Re to 0.71. Sensitivity analysis identified transmission (0.5) and cost-driven treatment avoidance (0.08) as key drivers

The findings suggest that scaling ITN and ACT coverage to about 40% could lower the effective reproduction number towards or below one, indicating reduced malaria transmission. Policymakers may therefore prioritize expanding affordable access to these interventions in high-burden settings, while noting that simplifying assumptions in the model limit generalizability.

Keywords: Malaria modeling, SITR–SI model, IPTp-SP, ITN effectiveness, ACT treatment.

Introduction

Over 249 million cases and 608,000 deaths from malaria occurred in 2022, with sub-Saharan Africa accounting for more than 94% of the global burden (*World Malaria Report 2023*). Malaria continues to be one of the biggest public health concerns in the world (*World Malaria Report 2023*). According to WHO, Nigeria alone is responsible for 31.3% of malaria-related deaths and 26.6% of all malaria cases worldwide(*World Malaria Report 2024*). Numerous ecological and socioeconomic factors contribute to the spread of malaria, such as the existence of effective vectors, inadequate sanitation, and restricted access to medical care (Atusingwize et al., 2025). Malaria transmission is constant in Rivers State, Nigeria's Niger Delta, and is exacerbated by inadequate drainage and a high vector density (Egbom et al., 2022). Malaria remains hyperendemic throughout Nigerian states despite years of international and domestic intervention efforts, indicating ongoing difficulties with control and elimination tactics (*Malaria Still Endemic in Nigeria despite Multibillion Naira Funding*).

The significance of successful malaria prevention and control measures is demonstrated by a wealth of evidence. The mainstays of malaria control around the world are the use of indoor residual spraying (IRS), long-lasting insecticidal nets (LLINs), intermittent preventive treatment during pregnancy (IPTp), and prompt administration of artemisinin-based combination therapies (ACTs). Through its National Malaria Elimination Programme (FMoH, 2020), Nigeria has put these strategies into practice; however, obstacles still stand in the way of attaining the best possible coverage and utilization. The most widely used vector control method in Rivers State is LLINs, which are frequently given out at prenatal appointments and during child health initiatives. According to data from Emohua LGA, after intensive LLIN campaigns, the prevalence of malaria dropped dramatically from over 40% to 8% (Okoro et al., 2024). However, because of financial and logistical limitations, IRS and larval source management are still mainly underutilized (Ogbonna, 2024).

However, because of financial and logistical limitations, IRS and larval source management are still mainly underutilized (Ogbonna, 2024). National guidelines require parasitological diagnosis prior to administration of treatment strategies like ACTs, which are widely promoted. However, in reality, Rivers State has poor adherence to pretreatment diagnostic testing. With rising presumptive ACT use, testing rates among children under five years old decreased from 19.3% in 2013 to 8.7% in 2018 (Okoro et al., 2024). Similarly, only 62.8% of pregnant women receive at least two doses of IPTp-SP, indicating that coverage is still low (Tobin-West & Asuquo, 2013). Despite the fact that ACTs are the gold standard, access to them is limited by their availability and cost in both the public and private sectors, which results in a persistent dependence on antiquated medications such as chloroquine (Ogbonna, 2024). These gaps show that although there are tools for controlling malaria, their fidelity of implementation is not at its best.

Previous research indicates that seasonal rainfall, humidity, and population movement all affect the spread of malaria in Nigeria. The disease is highly predictable and preventable if prompt interventions are put in place because of seasonal surges that occur during and after rainy months. These nationwide patterns, in which transmission peaks correspond with rainfall, are mirrored in Rivers State. Pre-seasonal planning is crucial for interventions like LLIN distribution and ACT availability, as evidenced by a SARIMAX model that used surveillance data from 2007 to 2021 and showed a significant correlation between rainfall and an increase in malaria incidence (Egbom et al., 2024). However, in practice, the timing and scope of interventions frequently fall behind epidemiological trends.

There are still a number of knowledge and practice gaps in spite of the policies and data that are available. The majority of research focuses on clinical outcomes or intervention coverage, but it doesn't assess how various interventions interact dynamically to reduce transmission. Furthermore, few studies have quantitatively evaluated how combined strategies like ITN coverage, ACT use, and IPTp uptake affect the spread of malaria in geographically distinct, high-burden regions like Rivers State. Additionally, there is are limited modeling evidence that is specific to regional epidemiological contexts to inform policy design and resource prioritization. Therefore, by simulating scenarios, estimating disease burden under different intervention levels, and identifying the best combinations for malaria control, a systems approach utilizing mathematical modeling can aid in filling these gaps.

In order to assess the combined effects of treatment, ITN usage, and IPTp-SP coverage in Rivers State, this study aims to provide an answer to the following research question: How can a compartmental model simulate malaria transmission dynamics, prevention and control strategies and treatment mechanism? It specifically looks into which factors have the biggest effects on the basic reproduction number (R_0) and how various intervention coverage scenarios change infection trends over time.

A deterministic compartmental SITR–SI model was created in order to answer this question. It represented vectors as Susceptible (S_v) and Infected (I_v), and human populations as Susceptible (S_h), Infected (I_h), Treated (T_h), and Recovered (R_h). Locally calibrated parameters for disease-induced mortality, birth and death rates, treatment uptake, prevention coverage, and behavioral constraints such as financial barriers were all included in the model. Ordinary differential equations were used to model compartment transitions, capturing the ongoing dynamics of malaria control and spread in the population.

The main objectives of this study were to simulate malaria transmission using a mathematical model, optimize treatment strategies such as ACT and community case management, assess the impact of ITN and IPTp-SP coverage on disease transmission, evaluate the role of financial constraints in treatment avoidance, and identify key transmission drivers influencing R_0. The findings aim to support malaria control policy formulation in Rivers State through modeling-based evidence, guiding more effective, timely, and equitable deployment of interventions.

Method

Study Site and Population

This study was conducted in Rivers State, located in the Niger Delta region of southern Nigeria, between latitudes 4°45'N and 5°15'N and longitudes 6°30'E and 7°15'E. It covers an estimated area of 11,077 square kilometers and is bordered by Imo, Abia, Anambra, Akwa Ibom, and Bayelsa states. With an estimated population of 7.4 million as of 2023, the state is among the most densely populated in Nigeria. Rivers State has a humid tropical climate characterized by high temperatures, heavy rainfall, and perennial river systems, which create an ideal breeding environment for Anopheles mosquitoes, the primary malaria vectors. The rainy season extends from March to October, peaking between June and September, while the dry season lasts from November to February. These climatic and geographic features sustain year-round malaria transmission with seasonal intensification. Malaria is endemic across all 23 Local Government Areas (LGAs) of the state, with vulnerable populations such as pregnant women, children under five, and rural communities disproportionately affected (Egbom et al., 2022; *World Malaria Report 2023*, 2023).

Data Sources

Epidemiological Data

This study utilized monthly malaria case reports and incidence data from Rivers State, covering a six-year period (2018–2023). Data were sourced from the District Health Information System 2 (DHIS2), the official national health data repository that aggregates routine health facility reports across Nigeria. DHIS2 data include confirmed malaria cases by microscopy and Rapid Diagnostic Tests (RDTs), as well as treatment uptake using Artemisinin-based Combination Therapies (ACTs). Additional epidemiological indicators such as Intermittent Preventive Treatment in pregnancy (IPTp) uptake, ITN ownership and usage, and malaria-related hospital admissions were obtained from the Nigeria Malaria Indicator Survey (NMIS 2021) and the National Demographic and Health Survey (NDHS 2018). Population figures, including the number of pregnant women and women of reproductive age in Rivers State, were retrieved from the National Population Commission.

Entomological Data

Vector-related parameters, including mosquito lifespan, biting rates, and transmission probabilities, were extracted from peer-reviewed literature and reports by the World Health Organization (WHO, 2023).

Model Formulation

Description of the Model

A deterministic compartmental model was developed to simulate malaria transmission dynamics in Rivers State. The model stratifies the human population into four compartments: Susceptible (S_h), Infected (I_h), Treated (T_h), and Recovered (R_h). The mosquito population is divided into Susceptible (S_v) and Infected (I_v) classes. The model tracks transitions between these compartments over time due to infection, treatment, recovery, and death.

Classification of Human Compartments

i. ***Susceptible Humans (S_h):*** This compartment includes individuals who are healthy and not yet infected with malaria and humans who have been healed malaria and eventually lost their immunity. They can become infected after being bitten by an infected mosquito. The rate of infection depends on the transmission rate, prevention by ITNs and IPTp-SP, and the density of infected mosquitoes.

ii. ***Infected Humans (I_h)*** This group includes individuals who have contracted malaria but have not yet been treated. They may recover naturally, seek treatment, or die due to the disease. They also contribute to further transmission by infecting mosquitoes.

iii. ***Treated Humans (T_h)*** These are individuals currently undergoing treatment for malaria. They exit the infected class upon seeking treatment. Financial constraint might hinder their treatment thereby reducing the treatment rate. Treated individuals may either recover, have treatment resistance, die naturally or due to treatment complications.

iv. ***Recovered Humans (R_h)*** This compartment consists of individuals who have recovered from malaria, either naturally or after receiving treatment. Some individuals in this group may die naturally or loss immunity and return to the susceptible class.

Classification of Mosquito Compartments

i. ***Susceptible Vectors (S_v)*** These mosquitoes are uninfected but can become infected upon biting an infected human. They are recruited into the population at a constant rate.

ii. ***Infected Mosquitoes (I_v)*** Mosquitoes in this class are carriers of the malaria parasite and can transmit the infection to susceptible humans. They remain infectious for life and may die from natural causes or disease-induced effects.

Model Assumptions

- The human and mosquito populations are non-constant, with recruitment rates (λ_h for humans, λ_v for vectors) and natural mortality rates (μ_h, μ_v).
- A proportion of newly born humans (ε_h) and vectors (ε_v) are vertically infected at birth from infected mothers.
- The population mixes homogeneously, such that each susceptible human has equal probability of being bitten by an infectious mosquito, and vice versa.
- Infected humans may:
    - Recover naturally at rate τ_h,
    - Receive treatment at rate α_h and recover due to treatment at rate γ_h,
    - Die due to the disease (δ_h) or from complications of treatment (η_h),
    - Remain infectious due to treatment failure or drug resistance at rate σ.
- Malaria prevention strategies influence transmission dynamics:
    - Insecticide-treated net (ITN) usage reduces effective contact at rate ψ_h,
    - Intermittent preventive treatment in pregnancy (IPTp-SP) reduces transmission at rate ρ_h,
    - Treatment avoidance due to financial constraint (π_h) affects treatment rate.
- Recovered individuals lose immunity at a constant rate (θ_h) and return to the susceptible class.
- There is no latent (exposed) class; newly infected individuals become immediately infectious.
- Vector population dynamics are governed by transitions between susceptible and infected states, with infection occurring through contact with infectious humans.
- Infected vectors die naturally at rate μ_v or from disease-related causes at rate δ_v.

- All compartment transitions occur in continuous time using a system of ordinary differential equations, implying instantaneous and smooth changes in state.

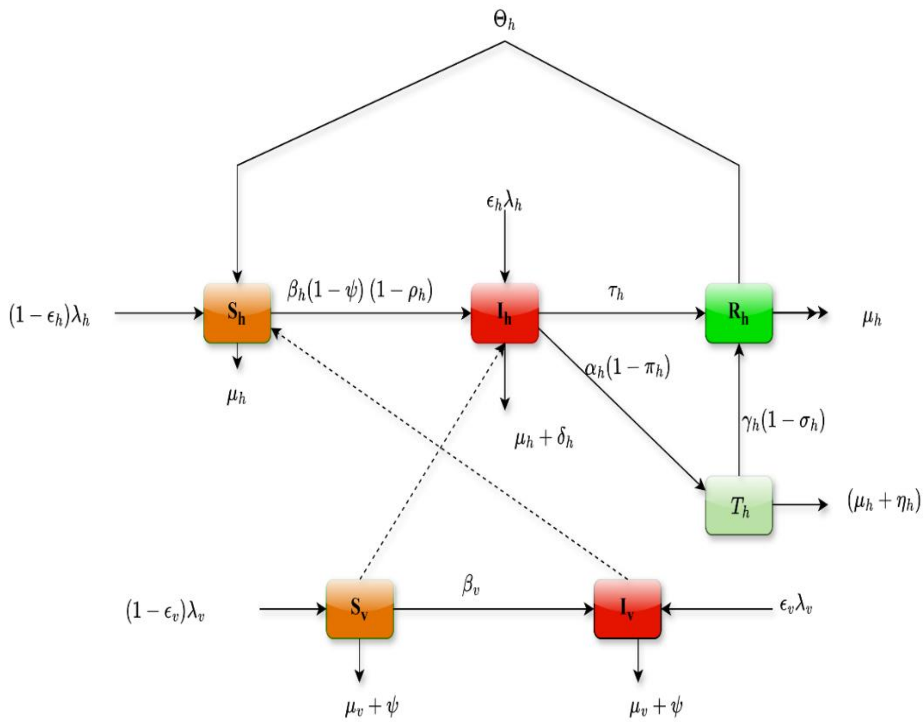

Fig 1.0 Schematic Flow Diagram of the Malaria Model

Table 1: Model Parameters

Parameter	Symbol	Value Used	Justification	Data Source
Human recruitment rate	λ_h	5342/day	3% annual growth of 6.5M: (0.03 × 6,500,000)/365	Nigeria NPopC projection (2023); WHO (2023)(*World Malaria Report 2023*, 2023)
Vector recruitment rate	λ_v	1,000,000/day	Scaled for ~1 vector per human (intense transmission)	WHO Entomology Guidelines; Model assumption
Human infection rate	β_h	0.5	Calibrated to fit high prevalence (~56%)	Eze et al. (2014); Smith et al. (2007)
Vector infection rate	β_v	0.4	Reflects sustained human-to-vector infectivity	WHO (2023); malaria modeling literature
Natural human death rate	μ_h	0.00063/day	Crude death rate ~4.3 per 1,000/year = 1/(4.3×365)	World Bank Nigeria mortality stats
Mosquito death rate	μ_v	0.05/day	Average lifespan of mosquito ≈ 20 days	WHO entomology data

Malaria-induced death (humans)	δ_h	0.005/day	~0.5% case fatality among untreated/severe	WHO Malaria Report (2023)
Treatment rate	α_h	0.1/day	10% of infected receive treatment daily	Assumed based on ACT availability & delay
Treatment failure rate	σ_h	0.2	~20% failure due to resistance or poor adherence	Oboh et al. (2024); Omoya & Oduro (2024)
Proportion of Treatment Avoidance Due to financial Constraint	π_h	0.16	In a **community-based survey of 624 urban households in Rivers State, 16.3% experienced catastrophic health expenditure** thereby avoid treatment.	Enuagwuna et al., 2024
Recovery rate (treated)	γ_h	0.15	Avg recovery in 7 days ⇒ 1/7 ≈ 0.14	WHO Clinical Guidance
Natural recovery rate	τ_h	0.005/day	Average duration of untreated malaria infection: approximately 200 days = 1 / 200 = 0.005 per day.	White et al. (2011)
Treatment-induced death	η_h	0.001	Rare, but included to capture serious ADRs	WHO/CDC reports
ITN effectiveness	ψ	0.15	~15% LLIN usage in Rivers (MIS 2021)	Nigeria MIS (2021); WHO (2023)
IPTp-SP effectiveness	ρ_h	0.32	IPTp (≥2 doses) uptake ~32% in Rivers	Tobin-West & Asuquo (2013); NMIS 2021

Table 1 (contd): Model Parameters

Parameter	**Symbol**	**Value Used**	**Justification**	**Data Source**
Congenital infection (human)	ϵ_h	0.01	1% congenital transmission	WHO, CDC reports
Congenital infection (vector)	ϵ_v	0.005	Assumed rare: 0.5%	WHO Vector Biology
Immunity loss rate	θ_h	0.0055	6 months immunity ⇒ 1/180 ≈ 0.0055	WHO Malaria Immunity Reports

Mathematical Formulation of the SITR Model

Let the human population at time t be denoted as S_h, and the mosquito population as S_t.

The model is governed by the following system of nonlinear ordinary differential equations:

1. Susceptible Humans S_h

$$\frac{dS_h}{dt} = (1-\epsilon_h)\lambda_h + \theta_h R_h - \frac{\beta_h S_h I_v (1 - \psi)(1-\rho_h)}{N_h} - \mu_h S_h$$

2. Infected Humans I_h

$$\frac{dI_h}{dt} = \epsilon_h \lambda_h + \frac{\beta_h S_h I_v (1-\psi)(1-\rho_h)}{N_h} - \alpha_h(1 - \pi_h)I_h - \tau_h I_h - \delta_h I_h - \mu_h I_h$$

3. Treated Humans T_h

$$\frac{dT_h}{dt} = \alpha_h(1 - \pi_h)I_h - \mu_h T_h - \eta_h T_h - \gamma_h(1 - \sigma_h)T_h$$

4. Recovered Humans R_h

$$\frac{dR_h}{dt} = \tau_h I_h + \gamma_h(1 - \sigma_h)T_h - \mu_h R_h - \theta_h R_h$$

5. Susceptible Vectors S_v

$$\frac{dS_v}{dt} = (1-\epsilon_v)\lambda_v - \frac{\beta_v S_v I_h}{N_h} - \mu_v S_v - \psi S_v$$

6. Infected Vectors I_v

$$\frac{dI_v}{dt} = \epsilon_v \lambda_v + \frac{\beta_v S_v I_h}{N_h} - \mu_v I_v - \psi I_v$$

Model Analysis

$$F = \begin{bmatrix} -\frac{I_v S_h \beta_h (1-\psi)(1-\rho_h)}{(I_h+R_h+S_h+T_h)^2} & -\frac{I_v S_h \beta_h (1-\psi)(1-\rho_h)}{(I_h+R_h+S_h+T_h)^2} & \frac{S_h \beta_h (1-\psi)(1-\rho_h)}{I_h+R_h+S_h+T_h} \\ 0 & 0 & 0 \\ -\frac{I_h S_v \beta_v}{(I_h+R_h+S_h+T_h)^2} + \frac{S_v \beta_v}{I_h+R_h+S_h+T_h} & -\frac{I_h S_v \beta_v}{(I_h+R_h+S_h+T_h)^2} & 0 \end{bmatrix}$$

The disease-free equilibrium is the state at which no infection exists in the population, at disease free equilibrium, $I_h = T_h = R_h = I_v = 0$, $S_h = \frac{(1-\epsilon_h)\lambda_h}{\mu_h}$ $S_v = \frac{(1-\epsilon_v)\lambda_v}{\mu_v + \psi}$

$$F_{dfe} = \begin{bmatrix} 0 & 0 & \beta_h(1-\psi)(1-\rho_h) \\ 0 & 0 & 0 \\ \frac{\beta_v \lambda_v \mu_h (1-\epsilon_v)}{\lambda_h(1-\epsilon_h)(\mu_v+\psi)} & 0 & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} \alpha_h(1-\pi_h) + \delta_h + \mu_h + \tau_h & 0 & 0 \\ -\alpha_h(1-\pi_h) & \eta_h + \gamma_h(1-\sigma_h) + \mu_h & 0 \\ 0 & 0 & \mu_v + \psi \end{bmatrix}$$

$$(F_{dfe}V)^{-1} = \begin{bmatrix} 0 & 0 & \frac{\beta_h(1-\psi)(1-\rho_h)}{\mu_v+\psi} \\ 0 & 0 & 0 \\ -\frac{\beta_v\lambda_v\mu_h(1-\epsilon_v)}{\lambda_h(1-\epsilon_h)(\mu_v+\psi)(\alpha_h\pi_h-\alpha_h-\delta_h-\mu_h-\tau_h)} & 0 & 0 \end{bmatrix}$$

Reproduction Number (R_0)

The basic reproduction number (R_0) was derived analytically using the next-generation matrix method. It represents the expected number of secondary cases generated by one infected individual in a wholly susceptible population. An $R_0 > 1$ indicates sustained transmission, while $R_0 < 1$ suggests the potential for disease elimination.

$$R0 = \frac{\sqrt{-\frac{\beta_h\beta_v\lambda_v\mu_h(\epsilon_v-1)(\psi-1)(\rho_h-1)}{\lambda_h(\epsilon_h-1)(\alpha_h\pi_h-\alpha_h-\delta_h-\mu_h-\tau_h)}}}{\mu_v+\psi}$$

Sensitivity Analysis

A normalized forward sensitivity analysis was conducted to evaluate the relative impact of each parameter on R_0. This analysis helps identify the most influential factors affecting transmission dynamics and guides targeted intervention strategies.

Scenario Analysis

Scenarios were simulated to assess the impact of varying ITN coverage, treatment rates, and IPTp uptake on infection dynamics and R_0. Separate simulations for 2-dose and 3-dose IPTp-SP regimens were also evaluated to estimate their differential impact on transmission.

Results

Case Descriptive

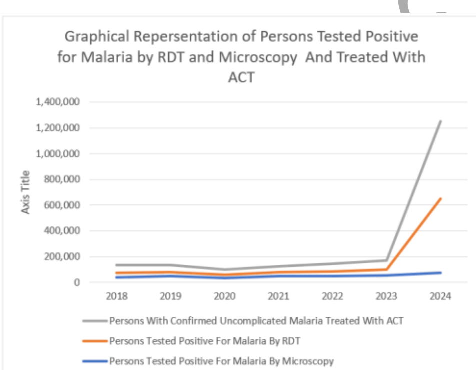

Figure 2: Source: National Malaria Data Repository, Nigeria 2025

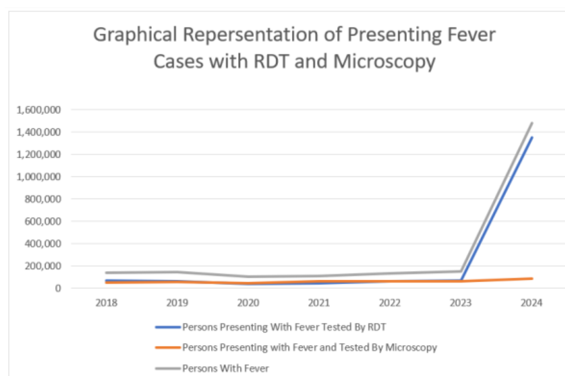

Figure 3: Source: National Malaria Data Repository, Nigeria 2025

Figure 2 shows a steady trend of confirmed uncomplicated malaria cases, RDT, and microscopy positives from 2018 to 2023, followed by an exponential surge in 2024. Confirmed cases of uncomplicated malaria treated with ACT jumped from 71,223 in 2023 to 598,490 in 2024. This sharp rise suggests a possible outbreak or improved surveillance/reporting.

Figure 3 displayed that fever cases and malaria testing in Rivers State remained relatively stable between 2018 and 2023, but in 2024, there was a drastic increase fever cases surged to 1.48 million, and over 1.4 million were tested. Positive RDT results rose to 578,986, with 598,490 treated using ACT. The significant 2024 spike may indicate increased transmission, improved case detection, or data quality issues.

$$R0 = \frac{\sqrt{-\frac{\beta_h \beta_v \lambda_v \mu_h (\epsilon_v - 1)(\psi - 1)(\rho_h - 1)}{\lambda_h (\epsilon_h - 1)(\alpha_h \pi_h - \alpha_h - \delta_h - \mu_h - \tau_h)}}}{\mu_v + \psi} = 1.9026$$

This result indicated that, on average, one infectious individual could generate approximately 1.9 new infections in a fully susceptible population. Since the R0R_0R0 value was greater than 1, the model suggested that malaria transmission would persist and potentially grow in the absence of intensified control measures. This implied that the current level of interventions (including ITN usage, treatment seeking, and IPTp-SP coverage) was insufficient to interrupt transmission, and stronger or more effective control strategies would be required to reduce R0R_0R0 below 1 and ultimately eliminate the disease.

Sensitivity Values of Model Parameters and Their Influence on Basic Reproduction Number (R0)

The sensitivity analysis showed that the human-to-vector transmission rate (βh=0.5) and vector-to-human transmission rate (βv=0.5) had the highest positive sensitivity values, indicating that increases in these transmission rates strongly increased the basic reproduction number (R0) and intensified malaria spread (fig 6). The treatment avoidance rate due to financial constraint (πh=0.0845) also had a positive sensitivity value, suggesting that economic barriers to treatment contributed to sustained transmission. Conversely, the treatment rate of infected individuals (αh=−0.04483), natural recovery rate (τh=−0.0264), and effectiveness of insecticide-treated nets (ψ=−0.0838) all had negative sensitivity values, meaning that improvements in these parameters helped lower R0. The uptake of intermittent preventive treatment in pregnancy (ρh=−0.2352) had the strongest negative effect on R0, highlighting its significant role in reducing transmission(Fig 8). These results emphasized the need for targeted interventions that both interrupt transmission and reduce barriers to effective treatment.

Table 2: Sensitivity Values of Model Parameters

Parameters	Sensitivity Values
β_h	0.5
β_v	0.5
α_h	-0.04483
π_h	0.0845
τ_h	-0.0264
ψ	-0.0838
ρ_h	-0.2352

Impact of ITN Usage and Treatment Rate on Basic Reproduction Number (R_0)

Table 3 presents a comparative sensitivity analysis of the basic reproduction number (R_0) under varying levels of **Insecticide-Treated Net (ITN) usage** and **treatment rate (α_h)**. The left section shows how increasing ITN coverage significantly reduces R_0, from 8.25 with no ITN usage ($\psi_h = 0$) to 0.71 at 40% usage ($\psi_h = 0.4$), indicating strong effectiveness in interrupting transmission. The right section shows that increasing the treatment rate from 5% to 30% also reduces R_0, though with less dramatic impact, from 2.55 to 1.14. These results underscore that ITN usage has a more immediate and stronger effect on lowering malaria transmission than increasing treatment rate alone, although both are important complementary strategies for achieving $R_0 < 1$.

Table 3: Impact of ITN Usage and Treatment Rate on Basic Reproduction Number (R_0)

ITN Usage Rate	R0	Treatment Rate	R0
0	8.2546	0.05	2.5512
0.1	2.6103	0.1	1.9026
0.15	1.9026	0.2	1.3848
0.25	1.1915	0.3	1.1421
0.4	0.7104		

Simulation Plots

Fig 4 illustrated the transmission dynamics among human compartments over time. Initially, the number of susceptible humans was highest but declined rapidly due to high infection pressure, primarily driven by a high transmission rate (βh=0.5). As treatment (αh=0.1) and recovery (γh=0.15) mechanisms took effect, the infected population reached an early peak and then began to decline. Treated individuals also increased early in the simulation and tapered off in line with declining infections. The recovered population showed a consistent increase as individuals exited the infected and treated states, eventually stabilizing due to immunity loss at rate θh.

Fig 5 showed vector transmission dynamics. Susceptible vectors increased sharply due to a high vector recruitment rate (λv=1,000,000 per day), mimicking an intense breeding cycle. The infected vector population rose quickly as vectors fed on infected humans but declined soon after due to high vector mortality (μv=0.05) and the moderating effect of ITNs (ψ=0.15). Despite control efforts, the large and fast-replicating vector population sustained malaria transmission.

Fig 6 demonstrated the effect of varying ITN effectiveness on infected human dynamics. When ITN effectiveness was absent (ψ=0), the infection peak was highest and lasted longest. As ITN usage increased to ψ=0.1 and ψ=0.25 there was a moderate reduction in infection levels. With high

ITN effectiveness (ψ=0.4), infection levels declined quickly and significantly. This suggested that the existing ITN coverage (ψ=0.15) was insufficient to interrupt malaria transmission in the population.

Fig 7 assessed the impact of treatment rate (αh) on infection levels. At low treatment rates (αh=0.05), infections remained high and resolved slowly. The baseline rate (αh=0.1) showed moderate infection control, while higher treatment rates (αh=0.2 to αh=0.3) resulted in rapid and sustained reductions in infections. These results emphasized the importance of increasing access to prompt and effective treatment to achieve malaria containment.

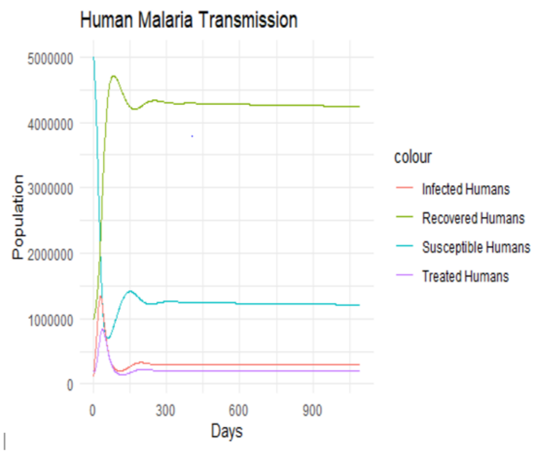

Fig 4: Human Malaria Transmission

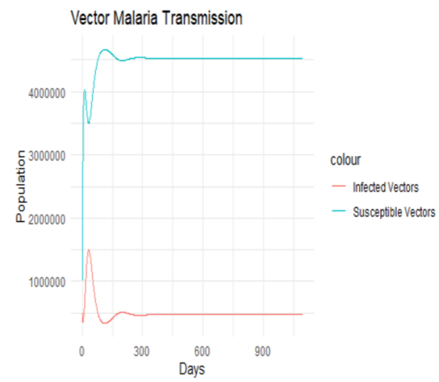

Fig 5: Vector Malaria Transmission

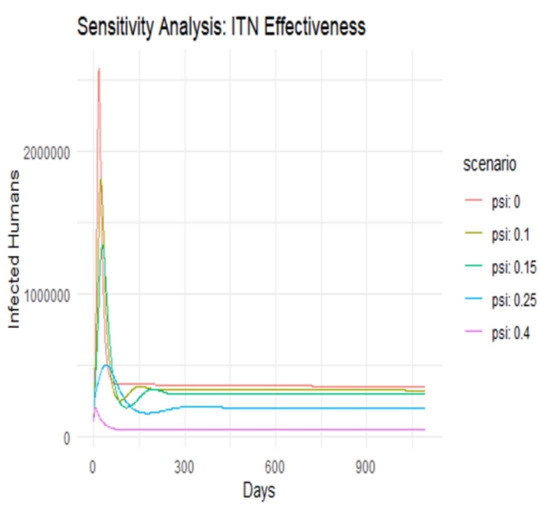

Fig 6: ITN Effectiveness Over Time

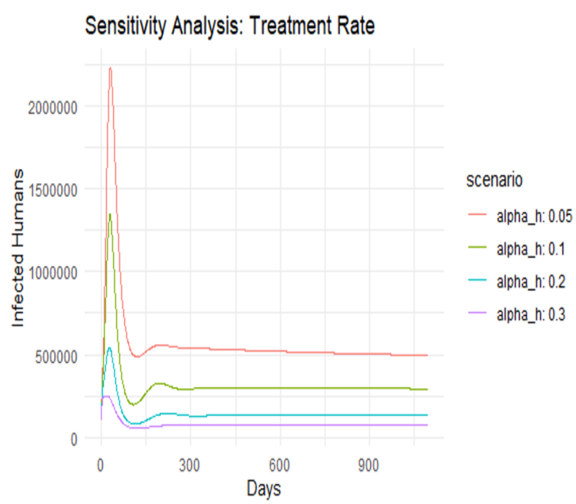

Fig 7: Treatment Rate Over Time

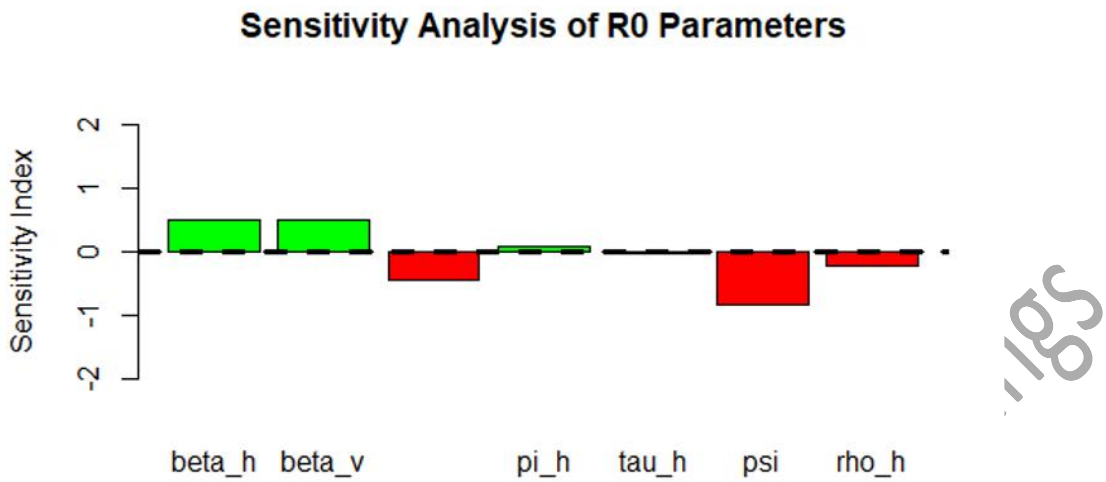

Fig 8: sensitivity Analysis of R0

Discussion

This study successfully developed and simulated a compartmental SITR-SI malaria transmission model to evaluate the impact of treatment, ITN usage, and drug-based interventions in Rivers State, Nigeria. The estimated basic reproduction number ($R_0 = 1.9026$) suggests that malaria transmission remains endemic, with the potential for sustained outbreaks if control efforts are not intensified. This finding aligns with prior studies reporting high malaria prevalence and transmission persistence in the region (Eze et al., 2014; Wogu & Nduka, 2018). The simulation results demonstrated that high human-vector transmission rates (β_h and $\beta_v = 0.5$), inadequate ITN coverage ($\psi = 0.15$), low treatment-seeking behavior due to financial constraints ($\pi_h = 0.0845$), and moderate treatment rates ($\alpha_h = 0.1$) are major contributors to continued transmission. These dynamics are consistent with local survey data highlighting poor adherence to the test-and-treat policy and gaps in IPTp-SP uptake (Oboh et al., 2024; Tobin-West & Asuquo, 2013).

The model's sensitivity analysis emphasized the critical role of intervention coverage in lowering R_0. IPTp-SP had the strongest negative influence on R_0, corroborating findings from Tobin-West and Asuquo (2013), who noted its effectiveness in reducing maternal and infant malaria burden when adherence is high. ITN effectiveness and treatment rates also contributed negatively to R_0, demonstrating their potential to curb transmission when scaled adequately. However, these strategies currently suffer from underutilization and logistical limitations, as also reported by

Omoya and Oduro (2024). The temporal trends observed from 2018 to 2025 in the simulation reflected a gradual decline in malaria burden, especially in infected and treated individuals, which may be attributed to incremental improvements in intervention coverage. However, the persistently high R_0 and large vector population indicate that these improvements are insufficient for elimination.

Simulations further demonstrated that enhancing ITN effectiveness from 15% to 40% could significantly reduce infection peaks, while increasing treatment rates substantially accelerated recovery and lowered prevalence. These results reinforce previous modeling studies recommending integrated approaches tailored to seasonal patterns (Uzoma & Sulaiman, 2023). The findings validate the critical need to align interventions with peak transmission seasons, ensure consistent net usage, and eliminate cost-related barriers to treatment access. Altogether, this model offers a robust framework for guiding data-driven decision-making and optimizing resource allocation in malaria control programs in Rivers State.

Recommendation

To effectively reduce malaria transmission in Rivers State, it is imperative to strengthen vector control measures by increasing the coverage and consistent usage of Long-Lasting Insecticidal Nets (LLINs). This can be achieved through routine net distribution programs complemented by sustained public education campaigns. Worn-out nets should be promptly replaced, and community-led awareness initiatives should be integrated to foster behavioral change and enhance net utilization at the household level.

Improving access to treatment is equally crucial. Financial barriers should be eliminated through the subsidization of Artemisinin-based Combination Therapies (ACTs) and the promotion of community-based case management approaches. Health insurance schemes must be expanded to include comprehensive malaria treatment coverage, particularly targeting vulnerable populations such as children under five and pregnant women.

Efforts to boost uptake of intermittent preventive treatment in pregnancy (IPTp-SP) should also be prioritized. This includes scaling up antenatal care outreach services and intensifying education on the importance of IPTp-SP adherence. Consistent drug availability across all primary health care centers must be ensured, and its administration should be reinforced as a routine component of antenatal care services. Additionally, enhancing malaria surveillance and diagnostic capacity is vital. This involves seasonal pre-positioning of diagnostic kits and antimalarial drugs in anticipation of transmission peaks, along with strict enforcement of the test-before-treat policy. Finally, the integration of predictive modeling into state-level malaria planning is recommended to optimize the timing and scale of interventions. By aligning control strategies with seasonal patterns and localized transmission hotspots, resources can be allocated more effectively for maximal impact.

Conclusion

This study developed and analyzed a malaria transmission model tailored to the epidemiological and intervention realities of Rivers State. The findings highlighted persistent transmission driven by inadequate intervention coverage and socio-economic barriers. With an R_0 of 1.9026, the model suggests that malaria elimination is not achievable under current control levels. Simulation and sensitivity analyses revealed that increasing ITN effectiveness, treatment coverage, and IPTp-SP uptake can significantly reduce disease burden. These results emphasize the need for integrated, scalable, and equity-focused strategies to strengthen malaria control and move towards elimination. Modeling remains an essential tool to support targeted interventions and evidence-based decision-making in high-burden settings.

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