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Malaria transmission dynamics and the impact of treatment interventions in Kano State, Nigeria: a compartmental model approach

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Abstract

Introduction: *malaria remains a significant public health burden in sub-Saharan Africa, with Kano State reporting over 6 million cases in 2022. Despite ongoing control efforts, malaria transmission persists due to climatic factors, inadequate healthcare infrastructure, and gaps in treatment access. Artemisinin-based combination therapy (ACT) is a widely recommended treatment. This study analyzed malaria transmission dynamics in Kano using a mathematical model to evaluate the impact of ACT coverage on disease control.* ***Methods:*** *this study utilized secondary data from the District Health Information System 2 (DHIS2) for the period 2018–2022 to estimate state variables and analyze trends, while key parameters were sourced from published research. A compartmental SITR-SI model was employed, with numerical simulations and sensitivity analyses conducted to assess the effects of varying ACT coverage levels.* ***Results:*** *the effective reproduction number (Re) for Kano State was estimated at 3.01, indicating high transmission potential. Model simulations revealed that increasing ACT coverage to 80% reduced the rate of resistance below 1, demonstrating the potential for disease control. Seasonal peaks in malaria incidence were observed during the rainy season. Sensitivity analyses confirmed that treatment coverage had the most significant influence on reducing transmission and infection duration.* ***Conclusion:*** *malaria control in Kano State requires scaling up ACT treatment coverage to at least 80% to effectively reduce transmission. Targeted interventions during seasonal peaks are essential for minimizing the disease burden and improving health outcomes.*

Introduction

Malaria is a life-threatening disease caused by Plasmodium parasites, which are transmitted to humans through the bites of infected female Anopheles mosquitoes [1]. It remains one of the most significant public health challenges globally, particularly in sub-Saharan Africa, where it is a leading cause of morbidity and mortality [1]. According to the World Health Organization (WHO), there were approximately 249 million malaria cases worldwide in 2022, resulting in an estimated 608,000 deaths, predominantly affecting young children and pregnant women in endemic regions [2]. Sub-Saharan Africa accounted for about 94% of these cases and deaths, underscoring the region´s disproportionate burden [3]. Nigeria alone contributes 27% of global malaria cases and 31% of deaths, making it the country with the highest malaria burden worldwide [4]. Nigeria represents a significant proportion of the global health malaria crisis, comprising 27% of worldwide cases and 31% of deaths in 2022 [5]. An estimated 6,088,000 malaria cases out of a population of approximately 15,300,000, equating to 40% of the total population, were reported in Kano State in 2022 [3]. This figure reflects a significant burden, as the state has been identified as having a high incidence of malaria cases [6]. Reports indicate that over 50% of outpatient visits in Kano State are due to malaria-related illnesses [7,8]. The burden of malaria is exacerbated by socio-economic factors, inadequate healthcare infrastructure, and climate variability, which collectively hinder effective control measures [9].

As of 2014, Africa contributed to global deaths by about 91%, underscoring the continent's vulnerability to this disease [2]. The interplay between environmental conditions and human factors has led to complex transmission dynamics. For instance, variations in temperature and rainfall significantly influence mosquito breeding patterns and the lifecycle of the Plasmodium parasite [10]. While treatment interventions, such as

artemisinin-based combination therapies (ACTs), remain the cornerstone of malaria control, insecticide resistance among mosquito populations and gaps in healthcare access and treatment adherence limit their effectiveness [11]. Recent studies highlighted that while progress has been made in reducing malaria incidence through various interventions, the emergence of drug-resistant strains and climatic changes pose new challenges for malaria control strategies across the continent [12].

Numerous studies highlighted the importance of achieving high treatment coverage for malaria management. Research indicates that increasing the use of artemisinin-based combination therapies (ACTs) to 80% can significantly reduce malaria transmission and outbreak duration [13,14]. In countries like Kenya and Zambia, widespread availability of malaria drugs has decreased malaria's impact by over 50%, particularly when combined with interventions such as insecticide-treated nets (ITNs) and indoor residual spraying [15]. Areas with treatment coverage above 70% have noted declines in malaria cases, as supported by findings from Tanzania and Uganda [16,17]. Malaria transmission is significantly influenced by climate and environmental factors, particularly in tropical regions. In Kano State, seasonal rainfall patterns create ideal breeding conditions for Anopheles mosquitoes [2].

Several mathematical models have proven useful for predicting malaria transmission dynamics and offering superior insights into the effectiveness of integrated strategies by simulating various scenarios [18,19]. These models can be formulated using biological data and experimental data to simulate the outcomes under different scenarios [4,20]. These include statistical regression models, which are useful for identifying risk factors and associations, and agent-based models, which simulate individual-level interactions to capture complex behavior and variability in malaria spread. However, these approaches often require large volumes of detailed input data and significant computational power, making them less feasible in low-resource settings [2]. In contrast, compartmental models such as SIR, SEIR, and SITR are widely used in malaria research because they offer a balance between biological realism and analytical simplicity [3].

In this study, the SITR-SI model was selected because it introduces a “treated” compartment, which enables the simulation of treatment effects, specifically the impact of artemisinin-based combination therapies (ACTs) on disease transmission. This structure has been effectively used in prior research to assess control strategies under various treatment coverage scenarios in high-burden settings [4]. Despite these existing modeling approaches, a clear gap remains in studies that incorporate ACT and other treatment interventions within a deterministic compartmental framework across all susceptible populations in high-burden settings like Kano State [2,4].

This study aimed to fill that gap by simulating the potential impact of these treatments in the context of Kano State. Understanding the interplay between population and treatment interventions is essential for addressing malaria transmission, where these variables create complex dynamics that influence the effectiveness of public health strategies. This study will provide targeted insights that can enhance malaria control strategies in Kano State, offering a valuable tool for policymakers and healthcare professionals aiming to mitigate this persistent public health threat.

Methods

Study area: this study focused on Kano State due to its exceptionally high malaria burden and its strategic relevance for malaria control in Nigeria. As Nigeria´s most populous state, Kano's epidemiological profile provides a robust basis for modeling interventions, with wide variation in malaria transmission across its 44 LGAs. The

availability of high-resolution, five-year data from DHIS2 further supports its suitability for detailed mathematical modeling. Importantly, while this study is Kano-specific, its findings can apply to other high-transmission, resource-constrained settings with similar environmental and health system characteristics. Kano State, situated in northern Nigeria, holds the distinction of being the most populous state in Nigeria and comprises 44 Local Government Areas (LGAs) [21]. The healthcare landscape in Kano State closely mirrors that of the entire nation, with infectious and parasitic diseases prevailing and accounting for most of both illness and death within the state [5,22]. There are a total of 1183 healthcare facilities spread across the 44 LGAs. Of the total health facilities, 97% (1142) constitute Primary Health Care (PHC) facilities while 3.3% and 0.2% fall under the Secondary Health Care (SHC) and Tertiary Health Care facilities, respectively [6,23]. Most of the healthcare facilities are publicly owned (91% primary, 85% secondary, 100% tertiary) [23].

Kano State, situated in northern Nigeria, holds the distinction of being the most populous state in Nigeria and comprises 44 Local Government Areas (LGAs) [21]. The healthcare landscape in Kano State closely mirrors that of the entire nation, with infectious and parasitic diseases prevailing and accounting for most of both illness and death within the state [5,22]. There are a total of 1183 healthcare facilities spread across the 44 LGAs. Of the total health facilities, 97% (1142) constitute Primary Health Care (PHC) facilities, while 3.3% and 0.2% fall under the Secondary Health Care (SHC) and Tertiary Health Care facilities, respectively [6]. Most of the healthcare facilities are publicly owned (91% primary, 85% secondary, 100% tertiary) [23].

Data collection: secondary data on monthly malaria incidence in Kano for the period of January 2018 to December 2022 were collected from the District Health Information System 2 (DHIS2) system. The sample for this study consisted of monthly malaria case records obtained from the DHIS2 platform for all 44 Local Government Areas (LGAs) in Kano State. Inclusion criteria were all available records of reported malaria cases, treatments administered (ACT and other antimalarials), and disaggregated data by LGA and month. Records with missing or incomplete treatment variables were excluded during data cleaning. This approach ensured comprehensive spatial and temporal coverage of malaria incidence and treatment patterns in the state. The data obtained from DHIS2 consists mainly of the incidence of monthly cases of malaria and treated patients. The data was cleaned and analyzed using Excel, Python, Google Colab, and R statistical software to identify the monthly trends, incidence by LGA, simulations, and scenario analysis of malaria cases over the study period. The data set had the following variables: Local Government Area (LGA), Persons with confirmed uncomplicated Malaria, Severe Malaria cases seen, Persons Clinically diagnosed with Malaria treated with ACT, Persons with Confirmed Uncomplicated Malaria treated with ACT, Persons with Confirmed Uncomplicated Malaria treated with other antimalarials, all disaggregated by the month and year.

Mathematical model

Model description: the model consists of two main components: the human population (SITR) and the mosquito population (SI). In the human population, susceptible individuals (S) can become infected (I) through contact with infected mosquitoes, move to the treated (T) compartment upon receiving treatment, or recover (R) naturally or through treatment. In the mosquito population, susceptible mosquitoes (S) become infected (I) after biting infected humans, with both compartments experiencing a natural death rate. Arrows in the schematic diagram indicate the flow between these compartments, along with the natural death rates affecting each group, and disease-induced death in the infectious human population.

Model assumptions: the model was developed based on the following assumptions: i) the total human and vector population is not constant, ii) development of malaria begins after a bite by a female Anopheles mosquito, iii) treatment with anti-malaria drugs is continuously given to infected humans, iv) after recovery, there is temporary immunity, v) control measures are continuously implemented, vi) Insecticide-treated Nets (ITNs) are continuously available/accessible, vii) indoor residual spray intervention works and leads to mosquito deaths, viii) the populations (human and vector) are non-negative, ix) malaria has an all-year-round transmission. Individuals from the human population move from one class to another as their disease status changes and as the disease evolves. Individuals enter the susceptible class through immigration or birth and leave through natural death or infection.

Model formulation: this study models malaria transmission dynamics using the SITR and SI models for humans, categorizing mosquitoes respectively. The model tracks population sizes over time (Nh) for humans and Nv for mosquitoes using ordinary differential equations (ODEs) with initial conditions. Figure 1 presents the schematic illustration of the model, with the arrows indicating the migration of the population dynamics considering treatment as an intervention. The malaria incidence was calculated from reported cases and treatment rates from data on patients treated with ACTs for uncomplicated and severe malaria. The values of the parameters for the model were obtained from existing literature, as shown in Annex 1 and Annex 2, except for the mosquito death rate, which we calculated based on the 42-day lifespan of female Anopheles mosquitoes using simple division [21,22].

$$\frac{dS_h}{dt} = \chi_h + \theta R_h - \frac{\beta_h S_h I_v}{N_h} - S_h \mu_h$$

$$\frac{dI_h}{dt} = \frac{\beta_h S_h I_v}{N_h} - (\mu_h + \sigma_h + \delta_h) I_h$$

$$\frac{dT_h}{dt} = \sigma_h I_h - (\mu_h + \alpha_h) T_h$$

$$\frac{dR_h}{dt} = \alpha_h T_h - (\mu_h + \theta) R_h$$

$$\frac{dS_v}{dt} = \chi_v - \frac{\beta_h S_v I_h}{N_h} - S_v \mu_v$$

$$\frac{dI_v}{dt} = \frac{\beta_v S_v I_h}{N_h} - \mu_v I_v$$

The state variables in Annex 1 were derived from the original dataset and the National Population Commission. The variables are Persons with confirmed uncomplicated Malaria, severe Malaria cases seen, persons clinically diagnosed with malaria treated with ACT, and persons with confirmed uncomplicated malaria treated with ACT. Annex 2 was created based on epidemiological studies and enhanced through Monte Carlo estimation, a technique proven in infectious disease modeling by integrating stochastic uncertainty into likelihood-based analysis. All malaria cases were categorized as infectious, and all treated cases were categorized as treated. The initial susceptible population is the total population in the first year of the study minus the initial infected individuals, and the vector population was calculated as three times the total population [24].

Equations for the SITR-SI model: based on the stated assumptions, the system of Ordinary Differential Equation (ODE) was adopted to develop simple SITR-SI model equations, which allow for to simulation of the spread of malaria and the impact of treatment. The equations formulated are:

Parametric values were all collected from literature, as represented in Annex 1 and Annex 2, excluding the death rate of mosquitoes, which was calculated from the Anopheles female mosquito life span of 42 days [25,26]. The state variables were calculated from the original data set and the National Population Commission document [26]. The incidence rate was calculated using the formula [25]:

Model analysis

Equilibrium states of the model: a disease system has two possible equilibria, a situation where both human and mosquito populations are free from infection, where:

$$\frac{Number\ of\ new\ infected\ cases}{Number\ of\ susceptible\ individulas}\ x\ 1000$$

This indicates the point at which there is no malaria infection. Where Ih = 0 and Iv = 0 [9]. Represented as:

$$\frac{dS_h}{dt} = \frac{IhSv\beta_h}{Ih+Rh+Sh} = 0$$

At rate of transfer:

$$\frac{dS_v}{dt} = 0$$

And secondly, the endemic equilibrium P* = (x*, y*). Where [26]:

$$X^* = \frac{IhSv\beta_h}{Ih+Rh+Sh}\ ,\ Y^* = \frac{IvSh\beta_v}{Ih+Rh+Sh}$$

Determination of the effective reproduction number: second generation matrix using the Jacobian method was used to calculate the effective reproduction number. The effective reproduction number, represented by *R*e, is the number of secondary infections caused by an infected individual throughout the course of a disease when everyone in the population is susceptible, with interventions in place [27].

In the six states variables, only Ih and Iv are the disease states variables. The disease and transfer states are given by F and V, respectively.

$$F= \begin{bmatrix} \beta_h & 0 \\ 0 & \beta_v \end{bmatrix} \text{ and } V= \begin{bmatrix} \delta_h & 0 \\ 0 & \mu_v \end{bmatrix}$$

The next generation matrix (G) was calculated using the matrix FV-1 [Ref], which is given by:

$$G = \begin{bmatrix} \frac{\beta_h}{\delta_h} & 0 \\ 0 & \frac{\beta_v}{\mu_v} \end{bmatrix}$$

While the effective reproduction number was estimated from the largest eigenvalue of G given by Li MY [26]:

$$R0 = \frac{\beta_v}{\mu_v}$$

Existence of disease-free equilibrium solutions: the effective reproduction number is a parameter that measures the existence and stability of a disease in a population. Where R_0 is ≤ 0, then the system has a disease-free equilibrium, but if R_0 is ≥ 1, there is a unique endemic equilibrium [27].

$$F= \begin{bmatrix} \beta_h & 0 \\ 0 & \beta_v \end{bmatrix}$$

Sensitivity and scenario analysis: sensitivity analysis was also done using Colab to determine the infectivity of the effective reproduction number using different parameters. This helps to determine how changes in this recruitment rate impact *R*e. Also, scenario analysis was performed using the ODE solver in R, to check for the different effects of treatment on the population,

by adjusting the value to different numbers from the initial 0.5% to 0.9%.

Results

Figure 2 shows a clear seasonal pattern in malaria cases in Kano State from January 2018 to December 2022. There are noticeable peaks every 12 months, starting from June, indicating higher transmission rates. The cases continue to peak around August to September, which coincides with the height of the rainy season, when malaria transmission is at its highest due to increased breeding of mosquitoes [10]. The data suggest that targeted interventions should be implemented starting in June to mitigate the rise in cases. This was the rationale for developing a compartmental model to check the effect of treatment on the infected population. Figure 3 shows the geospatial analysis of malaria incidence in Kano State for 2023 identifies three high-burden Local Government Areas (LGAs): Kano Municipal, Shanono, and Madobi, with prevalence ranging between 26 to 32%. These LGAs exhibit the highest malaria burden, highlighting significant spatial clustering of malaria incidence within the state

Numerical simulations: in this section, numerical simulations are considered to explore transmission dynamics. Figure 4 illustrates how the number of susceptible humans changes over time. I-Human starts with a higher number of susceptible individuals and declines slowly, indicating a gradual reduction in susceptibility. The T-human population begins at a lower point and drops quickly to almost zero, suggesting that this group experiences a faster decrease in susceptibility due to more effective treatment. This trend suggests the effectiveness of treatment and control measures. It also raises concerns about potential challenges, such as drug resistance or barriers to healthcare access and seeking medical assistance in the long run. Furthermore, the sudden rise in the number of people treated and their potential return to the susceptible population could lead to future outbreaks, underscoring the importance of continuous efforts in intervention and prevention measures [28].

Figure 5 illustrates the dynamics of the susceptible vector population (S-vector) and the infected vector population (I-vector) over 60 months. Initially, the S-vector population starts at approximately 200 per 1000, rapidly declines within the first 10 months, and then decreases gradually. Conversely, the I-vector, starting at around 50 per 1000, peaks at 10 months and subsequently declines steadily. This pattern suggests a high initial number of susceptible vectors, which quickly decrease due to infection or other factors. Over time, both populations decline, indicating potential control or recovery of the vector population, consistent with a disease transmission model suggesting effective vector management. There could be the reasons why the number of vectors has decreased, for instance improved efforts in controlling them with methods like using bed nets treated with insecticides and indoor spraying which target both susceptible and infected vector groups [29], changes in the environment like reduced rainfall or improved drainage that can decrease breeding grounds for vectors and hence lower their numbers; also factors in nature such as more predators could lead to a decline in vector populations over time [30].

Interpretation: the graphs likely model the interaction between humans and vectors, such as mosquitoes, in a disease transmission scenario. The rapid decline in susceptible vectors suggests they play a significant role in reducing the risk to humans.

Effective reproduction number: by applying equation 12 and using the values for μ_v and β_v obtained from literature Annex 1, a *R*e value of 3.01 was obtained. This suggests that, on average, each individual infected with malaria in Kano state is expected to infect approximately 3.01 other people, assuming no permanent immunity and available interventions. This indicates a

high potential for malaria transmission in the region [31]. This aligns with what might be expected in a highly endemic region with favorable conditions for mosquito breeding and transmission.

Sensitivity analysis - mosquito recruitment rate: to effectively lessen the effects of malaria in Nigeria, it's crucial to understand the factors that affect malaria transmission and occurrence. Studies have shown that the initial spread of the disease is connected to *R*e while the prevalence of the disease is influenced by the equilibrium point, specifically by the levels of infection [11]. The study had a negative value of -0.489 for the treatment rate when the sensitivity analysis test was calculated with respect to the treatment intervention. This analysis helps understand the influence of parameter values on the spread of diseases and helps identify if the intervention has an impact on *R*e [32].

Scenario analysis based on treatment intervention: scenario analysis shows that increasing the treatment rate from 50% to 70% and 80% reduces the effective reproduction number (Re) from 1.23 to 1.04 and 0.97, respectively.

Discussion

In this study, we evaluated the dynamics of the SITR-SI model and applied malaria transmission between humans and mosquitoes. The model incorporated demographic factors such as births and migration, which allowed infected individuals to re-enter the susceptible compartment, as well as the impact of treatment on the infected population. We derived the basic reproduction number and discussed the existence of stability of DFE and EE of the model (1,2,3,4,5,6) between susceptible humans and mosquitoes (10). The analysis showed that if *R*e is less than one, the disease-free equilibrium (DFE) is locally asymptotically stable. This implied that only the susceptible population remained, while the infected populations approached zero, leading to disease eradication. Conversely, if *R*e is greater than one, the DFE becomes unstable, indicating that humans and mosquitoes will get infected, as represented in equations (1)-(4) and (5)-(6), respectively. This has been verified numerically, with simulations presented in equations (8) and (10), and the results are illustrated in Figure 5.

The sensitivity analysis showed that the most effective parameter is ρ_h for the human compartment. The simulation showed that both humans and mosquitoes will exist and get infected. These results helped predict transmission and how preventive and control measures impacted the occurrence of malaria. Clearly, in the simulations, it was noticed that to reduce the *R*e, there was a need to focus on improved treatment in the infected population by increasing the coverage to higher levels, to reduce the rate of infection, represented shown graphically in Figure 4, Figure 5. From the simulations, it is evident that to reduce *R*e, we need to focus on improving treatment in the infected population by increasing coverage to higher levels, thereby reducing the rate of infection. This study presents a novel application of a SITR-SI compartmental model specifically designed to evaluate the impact of ACT treatment coverage on malaria transmission in Kano State, Nigeria, a high-burden and underrepresented region in malaria modeling literature.

Limitations: one limitation of this study was the reliance on secondary data, which could introduce inaccuracies in parameter estimates. Data cleaning and pre-processing were applied to minimize errors. Future research should focus on collecting primary data to validate model assumptions and improve accuracy.

Recommendations: i) increase ACT coverage to at least 80% to significantly reduce malaria transmission, ii) target high-burden LGAs like Fagge, Dala, and Gwale with intensified interventions, iii) deploy rapid diagnostic tests widely to promote early detection and treatment,

iv) use seasonal climate data to anticipate outbreaks and allocate resources proactively, vi) digitize health facility reporting to improve data accuracy and timeliness, v) establish a modeling unit within the Ministry of Health to guide malaria control strategies, vii) launch culturally tailored campaigns to improve net usage and prompt treatment-seeking behavior.

Conclusion

The model showed that malaria can be controlled effectively among infected populations by increasing the rate of coverage using treatment with ACT, which keeps the human population stable.

What is known about this topic

- *Malaria continues to be a significant health challenge in sub-Saharan Africa, particularly in Nigeria. In 2022, Kano State alone reported over 6 million cases, highlighting the difficulties posed by inadequate infrastructure, socioeconomic issues, and climate factors;*
- *Ensuring high coverage of ACT (artemisinin-based combination therapy) is essential for controlling malaria. Previous studies have demonstrated that achieving coverage levels above 70–80% significantly reduces both transmission and the duration of infection;*
- *Mathematical modeling is an established approach for simulating the dynamics of malaria transmission and has been employed to evaluate the effectiveness of interventions such as ACT, ITNs, and indoor spraying.*

What this study adds

- *This study presents the first detailed compartmental SITR-SI model specifically applied to malaria in Kano State, addressing a gap in region-specific modeling by incorporating treatment interventions such as ACT;*
- *The study identifies a high effective reproduction number (Re = 3.01) for Kano and shows that increasing ACT treatment coverage to 80% can reduce Re below 1, indicating the potential for malaria elimination;*
- *The analysis identifies seasonal and spatial trends in malaria cases, highlighting transmission peaks during the rainy season and pinpointing high-prevalence LGAs such as Kano Municipal, Shanono, and Madobi, thereby aiding in the targeting of interventions.*

Competing interests

The authors declare no competing interests.

Authors' contributions

Zainab Bello Dambazau prepared and wrote the initial draft, developed the algorithm for the model, and applied and computed the mathematical model. Karinate Cyril-Egware, Obi Charles, Gbenga Adegbite, supported the analysis and the algorithm development. Ganiyat Eshikhena coordinated the research activity planning and execution Dupsy Akoma, Nwadiuto Ojielo, Ezra Gayawan, Muktar Gadanya, Nafisah Ayinde Sikiru, Eze Nelson, critically reviewed and edited the manuscript. Chijioke Kaduru provided leadership of the project design, supervision of project delivery, and supervisory authorship of our manuscript. All the authors have read and agreed to the final version of this manuscript.

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Figures

Figure 1: schematic flow diagram of malaria transmission

Figure 2: trend of malaria cases in Kano 2018-2022

Figure 3: map showing prevalence of malaria in Kano, 2023

Figure 4: simulation of the infected and treated human population

Figure 5: simulation of susceptible and infected vector population

Annexes

Annex 1: state variables, their description, and their corresponding value (95 KB)

Annex 2: parameter description and its corresponding value (97 KB)

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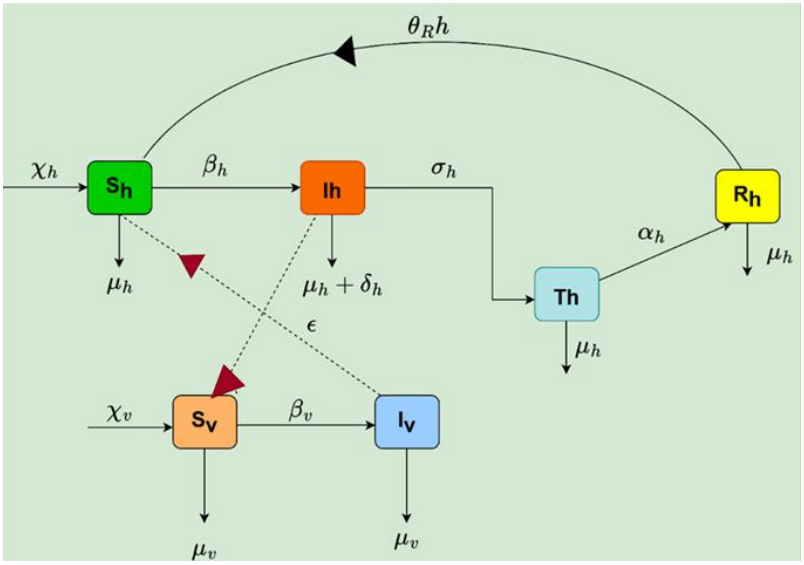

Figure 1: schematic flow diagram of malaria transmission

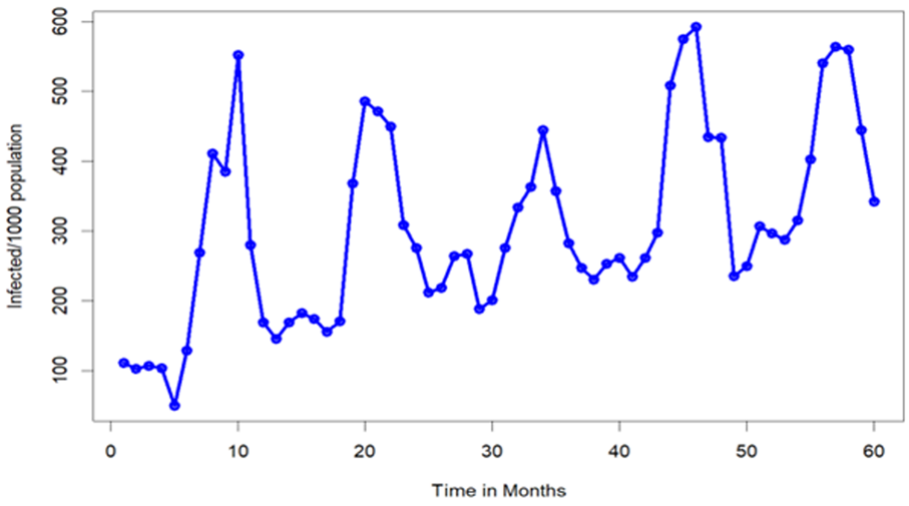

Figure 2: trend of malaria cases in Kano 2018-2022

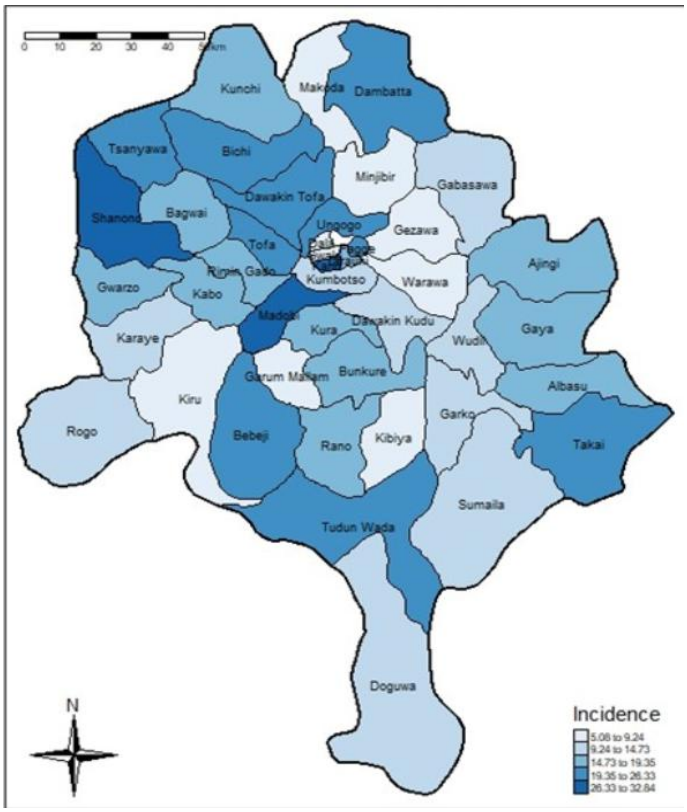

Figure 3: map showing prevalence of malaria in Kano, 2023

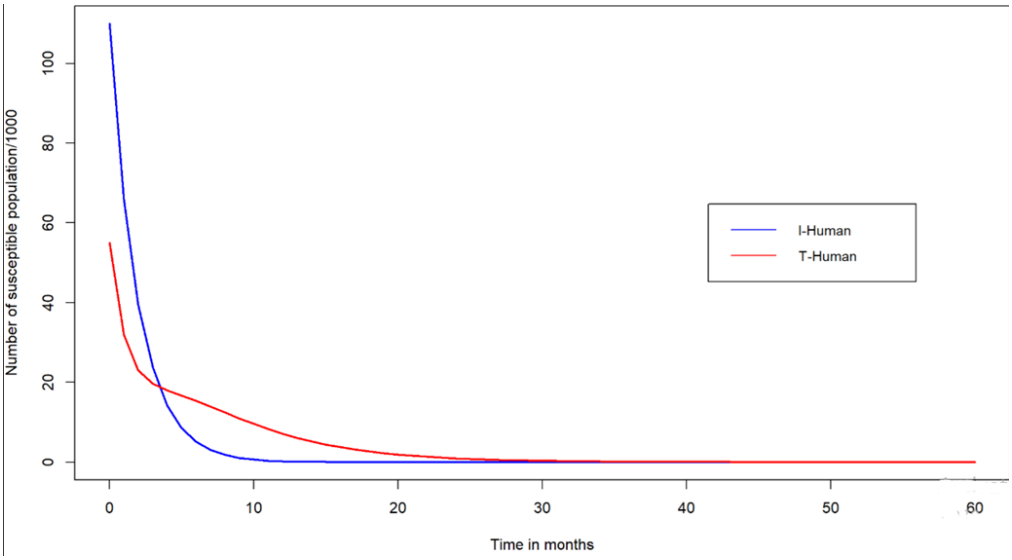

Figure 4: simulation of the infected and treated human population

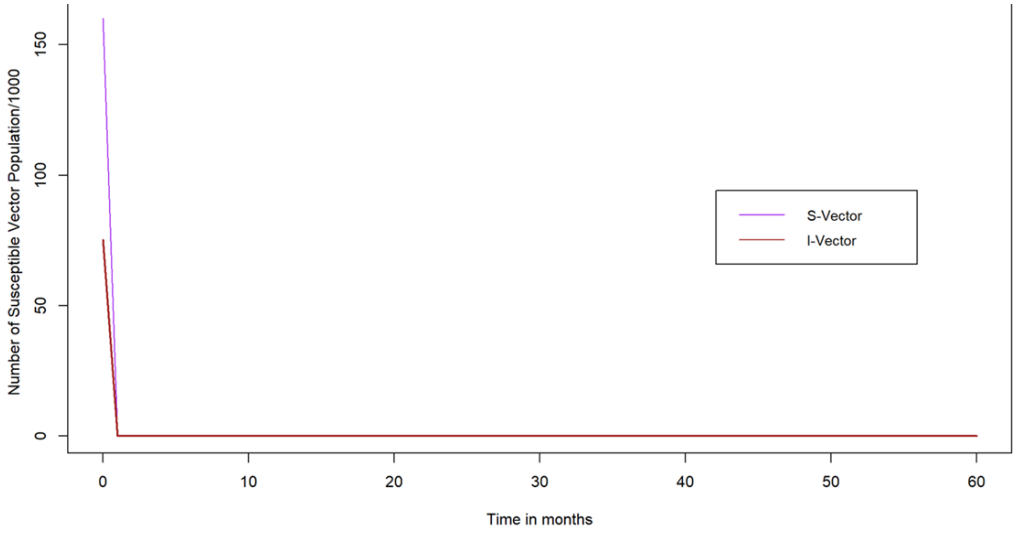

Figure 5: simulation of susceptible and infected vector population