

Mathematical Modeling of Temperature and Rainfall Driven Dengue Transmission in Sudurpashchim Province, Nepal

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Research Article

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ISSN: 3059-9504 (online)

DOI: <https://doi.org/10.3126/ajs.v2i1.87772>

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Article History

Received: October 16, 2025; Revised: December

01, 2025; Accepted: December 06, 2025;

Published: December 25, 2025

Keywords

SIR-SI model, basic reproduction number, disease free equilibrium, carrying capacity, transmission rate.

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ABSTRACT

Dengue disease dynamics highly depends on environmental temperature as its transmitting vectors-*Aedes aegypti* and *Aedes albopictus* mosquitoes are poikilothermal. Temperature influences mosquitoes' key traits, including biting rate, oviposition rate, development rates of aquatic and adult stages, and lifespan. Rainfall in proper amounts, together with suitable temperatures, significantly supports egg hatching and growth of aquatic stage by creating breeding sites. In regions like Nepal, where seasonal variations in temperature and rainfall occur, mosquito population fluctuates seasonally, causing vector-borne diseases like dengue fever to similarly rise and fall. This paper develops a climate-sensitive mathematical model for dengue transmission in Sudurpashchim Province, Nepal, integrating effects of seasonal change in temperature and rainfall on mosquito life traits. We analyze the dengue dynamics model using symbolic and numerical tools to better understand disease patterns. Numerical simulations indicate that increasing mosquito mortality and reducing carrying capacity of environment to limit aquatic phase population are effective strategies for controlling and diminishing dengue outbreaks.

1. INTRODUCTION

Vector-borne diseases such as dengue, Zika, and chikungunya continue to pose significant public health challenges globally, especially in tropical and subtropical regions. Among these, dengue is currently the most threatening vector-borne disease affecting human populations, imposing an estimated yearly infection burden of up to 400 million [1, 2]. Dengue fever is caused by the dengue virus, which exists in four serotypes (DENV1–DENV4), and is transmitted principally by *Aedes aegypti* and, less commonly, *Aedes albopictus* [3]. The transmission cycle follows a “human–mosquito–human” pattern primarily driven by mosquito bites. Dengue transmission is strongly influenced by climatic factors such as temperature and rainfall, which affect mosquito breeding, survival, and biting behavior. Although dengue transmission is mostly seasonal due to weather conditions, *Aedes aegypti* can sustain populations even in dry seasons under suitable temperatures, leading to potential year-round transmission.

Mathematical models have become invaluable tools in studying the transmission dynamics of vector-borne diseases and designing effective intervention strategies. Compartmental models, such as the SEIR–SEI frameworks developed by Esteva and Vargas [4] and Yang and Ferreira [5], form the foundation of vector-borne disease modeling by capturing host–vector interactions and human demography. Subsequent studies have extended these frameworks to incorporate environmental effects, particularly climate variables, to improve realism. For instance, Barsante et al. [6] developed and validated a rainfall driven model of *Aedes aegypti* populations, noting that additional climatic factors such as temperature and humidity should be included for better predictive performance. Johanson et al. [7] analyzed 20 years of data from Puerto Rico to

show significant associations between temperature, precipitation, and dengue transmission, while Morin et al. [8] developed a framework to model mosquito growth under climatic influences. Hii et al. [9] used weekly temperature and rainfall data for dengue forecasting. Furthermore, temperature-dependent mosquito traits like development and biting rates have been modeled using the Briere function [10] and quadratic functions [11, 12]. Vaidya and Wang [13] incorporated both seasonal and daily temperature variations in their biologically realistic model.

Motivated by these studies, our work aims to integrate both temperature and rainfall into a mathematical model to capture realistic mosquito population dynamics and dengue transmission patterns. We also focus on accounting for the under-reporting of infections, which remains a significant issue in dengue surveillance. In Nepal, over 90% of dengue cases go unreported due to asymptomatic infections or reporting barriers. In this paper, we formulate a model that incorporates the impacts of summer and rainy seasons on mosquito traits, as well as the phenomenon of under-reported dengue cases. The model is fitted to monthly dengue case data from 2024 in the Sudurpashchim Province of Nepal to estimate key epidemiological parameters and better understand local dengue dynamics.

2. METHODOLOGY

2.1 Data and Tools

We use demographic and epidemiological data, and climate information to formulate and analyze the SIR–SI dengue model with reported and non-reported infections. We manage raw case counts and climatic averages in Microsoft Excel. We perform

symbolic derivations, including the disease-free equilibrium, the basic reproduction number (R_0), and stability conditions, in Mathematica. We run numerical solutions, simulations, and plots in Python to solve the nonlinear differential equations and assess seasonal effects on dengue spread. We obtain monthly dengue case data from the Epidemiology and Disease Control Division (EDCD) of Nepal, demographic information from the 2021 Nepal Census, and climate data (temperature and rainfall) from the Department of Hydrology and Meteorology. These datasets provide the basis for model parameterization.

2.2 Mathematical Model

We formulate the SIR–SI compartmental model by dividing the human population into four compartments: susceptible humans (S_h), reported infectious humans (I_{hr}), non-reported infectious humans (I_{hn}), and recovered humans (R_h). The mosquito population is split into susceptible vectors (S_v) and infected vectors (I_v). We express the dynamics through a system of nonlinear ordinary differential equations, where climate-dependent functions adjust key

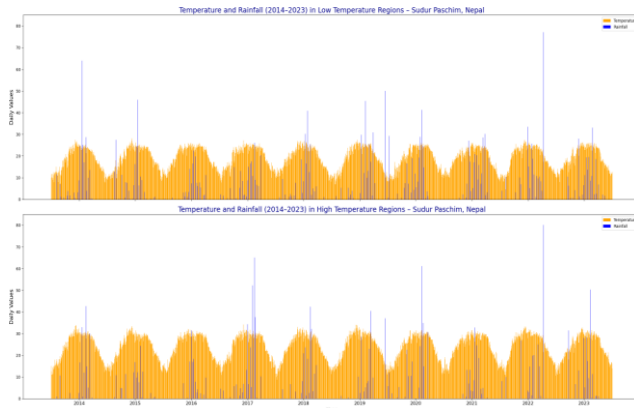


Fig. 1: Periodic pattern of temperature and rainfall in Sudurpashchim.

transmission and growth parameters. The model serves as the main research tool to study unreported infections, determine threshold conditions for disease persistence, and evaluate control strategies. Modeling climatic impacts dengue transmission is highly sensitive to environmental factors such as temperature and rainfall, which directly affect mosquito population dynamics and virus incubation times. To understand the climatic context of Sudurpashchim Province, we observed the pattern made by ten years of weekly meteorological data (2014–2023), specifically weekly average temperatures and total weekly rainfall.

Fig. 1 reveals a clear periodic pattern in both temperature and rainfall, with a one-year cycle. Significant rainfall is concentrated during the monsoon months (June to August), while summer months (April to September) exhibit high temperatures favorable for mosquito development, feeding frequency, and viral replication. This seasonal fluctuation in climatic variables directly motivates our inclusion of periodic effects in the transmission model. In particular, high summer temperatures enhance mosquito biting rate, survival, and viral transmission efficiency while monsoon rainfall increases mosquito breeding sites, thus temporarily boosting the vector carrying capacity.

To further support this, we analyzed the 2022 weekly data of temperature, rainfall, and reported dengue cases in

Sudurpashchim.

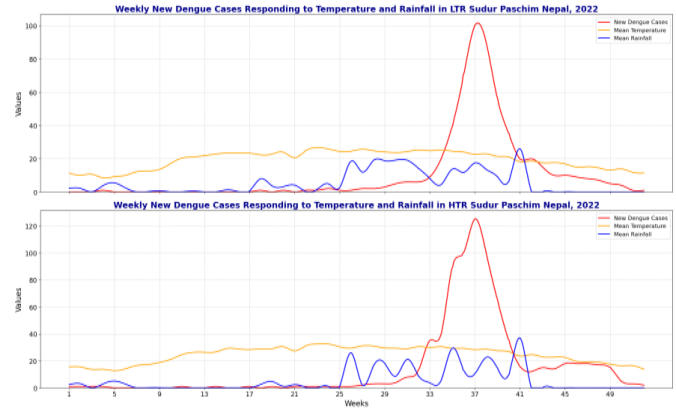


Fig. 2: Dengue trend in 2022 with respect to temperature and rainfall.

As shown in Fig. 2, dengue incidence in 2022 increased sharply starting mid-summer and peaked several weeks after the end of the monsoon season. This lag between rainfall and dengue outbreak is a typical pattern in dengue epidemiology and reflects the life cycle delay between vector proliferation and disease transmission.

These climatic realities of Sudurashchim strongly support the necessity of incorporating seasonal variation in temperature into the vector growth rate r , the transmission rates β_h (from vector to human) and β_v (from human to vector), and the seasonality of rainfall on the carrying capacity K_v in our mathematical model. Thus, we introduce seasonally modulated parameters using scaling factors to better capture the climatic influence on dengue dynamics. Let β_{h0} , β_{v0} and r_0 be baseline values of β_h , β_v and r , respectively, for off-summer season. Now, we define

$$\beta_h = (1 + \eta_1) \beta_{h0}, \quad \beta_v = (1 + \eta_2) \beta_{v0}, \quad r = (1 + \eta_3) r_0 \quad (2.1)$$

where $\eta_1, \eta_2, \eta_3 = 0$ for off-summer time and are some positive constants scales to the rates respectively in average due to warmth in summer. Similarly, we define

$$K_v = (1 + \alpha) K_{v0}, \quad (2.2)$$

where K_{v0} denotes off-monsoon carrying capacity (indicating overall space including breeding sites during aquatic stages) and α is additional positive scale to the carrying capacity due to rainfall. Other parameters used in the model are defined as follows. The symbol Λ_h represents the recruitment rate of humans, while μ_h and μ_v denote the natural death rates of humans and vectors, respectively. The parameter γ_h stands for the human recovery rate (Fig. 3). The transmission rate from vector to human is represented by β_h , and the transmission rate from human to vector is denoted by β_v . The symbol θ indicates the proportion of reported infections, r represents the mosquito growth rate, and K_v denotes the carrying capacity for vectors.

Model Equations

$$\frac{dS_h}{dt} = \Lambda_h - \frac{\beta_h I_v}{N_h} S_h - \mu_h S_h \quad (2.3)$$

$$\frac{dI_{hr}}{dt} = \theta \frac{\beta_h I_v}{N_h} S_h - \gamma_h I_{hr} - \mu_h I_{hr} \quad (2.4)$$

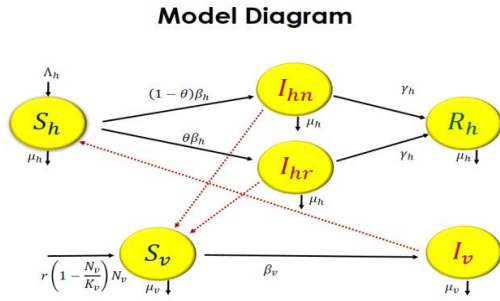


Fig. 3: SIR-SI dengue model with temperature and rainfall impacts.

$$\frac{dI_{hn}}{dt} = (1 - \theta) \frac{\beta_h I_v}{N_h} S_h - \gamma_h I_{hn} - \mu_h I_{hn} \quad (2.5)$$

$$\frac{dR_h}{dt} = \gamma_h (I_{hr} + I_{hn}) - \mu_h R_h \quad (2.6)$$

$$\frac{dS_v}{dt} = r \left(1 - \frac{N_v}{K_v} \right) N_v - \frac{\beta_v (I_{hr} + I_{hn})}{N_h} S_v - \mu_v S_v \quad (2.7)$$

$$\frac{dI_v}{dt} = \frac{\beta_v (I_{hr} + I_{hn})}{N_h} S_v - \mu_v I_v \quad (2.8)$$

where $N_h = S_h + I_{hr} + I_{hn} + R_h$ and $N_v = S_v + I_v$.

2.3 Mathematical Analysis

To understand the qualitative behavior of the proposed model, we perform mathematical analysis involving well-posedness, equilibrium analysis, and stability. We use standard techniques from dynamical systems and epidemiological modeling as discussed in [14, 15, 16].

Uniqueness and Existence of Solution

The model equations represent a system of ordinary differential equations (ODEs) with continuously differentiable right-hand sides. By the Picard–Lindelöf theorem [14], there exists a unique solution for given initial conditions in a suitable domain.

Positivity and Boundedness of Solutions

Let all initial values be non-negative. The model ensures that all state variables remain non-negative for all $t > 0$. This can be shown by contradiction: if any variable reaches zero, its derivative is non-negative or bounded below, preventing it from becoming negative. We define the total human and mosquito populations:

$$N_h(t) = S_h + I_{hr} + I_{hn} + R_h \text{ and } N_v(t) = S_v + I_v.$$

Summing the human equations yields:

$$\frac{dN_h}{dt} = \Lambda_h - \mu_h N_h \Rightarrow N_h(t) \leq \frac{\Lambda_h}{\mu_h},$$

which ensures boundedness. Similarly, mosquito population N_v is regulated by logistic growth, bounded above by K_v . Disease-Free Equilibrium (DFE) The disease-free equilibrium (DFE) corresponds to the state where no infection is present in the population, i.e., $I_{hr}^* = I_{hn}^* = R_h^* = I_v^* = 0$. The human susceptible class at DFE satisfies: $\frac{dS_h}{dt} = \Lambda_h - \mu_h S_h \Rightarrow S_h^* = \frac{\Lambda_h}{\mu_h}$. For the mosquito population, we consider logistic growth given by:

$$\frac{dN_v}{dt} = r N_v \left(1 - \frac{N_v}{K_v} \right) - \mu_v N_v.$$

At DFE, all vectors are susceptible, so $N_v = S_v$. Setting the derivative to zero:

$$0 = r S_v \left(1 - \frac{S_v}{K_v} \right) - \mu_v S_v$$

$$\Rightarrow \frac{S_v}{K_v} = 1 - \frac{\mu_v}{r} \Rightarrow S_v^* = K_v \left(1 - \frac{\mu_v}{r} \right).$$

This shows that the mosquito population at DFE is strictly less than the carrying capacity, unless $\mu_v \ll r$. This expression is derived from logistic growth dynamics, as supported in [17]. Thus, the disease-free equilibrium is: $E^* = \left(\frac{\Lambda_h}{\mu_h}, 0, 0, 0, K_v \left(1 - \frac{\mu_v}{r} \right), 0 \right)$.

Basic Reproduction Number (R_0)

We compute R_0 using the next generation matrix (NGM) approach [15]. Take as infected compartments $x = (I_{hr}, I_{hn}, I_v)^T$. Write the system for these compartments in the form $\frac{dx}{dt} = F(x) - V(x)$ where F contains new infection terms and V contains transition terms. From the model, the new infection terms are

$$F_1 = \theta \frac{\beta_h I_v}{N_h} S_h, \quad F_2 = \frac{(1 - \theta) \beta_h I_v}{N_h} S_h,$$

$$F_3 = \frac{\beta_v (I_{hr} + I_{hn})}{N_h} S_v$$

and the remaining transition terms are

$$V_1 = (\gamma_h + \mu_h) I_{hr}, \quad V_2 = (\gamma_h + \mu_h) I_{hn}, \quad V_3 = \mu_v I_v.$$

We compute the Jacobians F and V of $(F_1, F_2, F_3)^T$ and $(V_1, V_2, V_3)^T$ at the E^* . Since at the DFE, $S_h^* = N_h^*$ and $S_v^* = N_v^*$, we obtain

$$F = \begin{pmatrix} 0 & 0 & \frac{\theta \beta_h S_h^*}{N_h^*} \\ 0 & 0 & (1 - \theta) \frac{\beta_h S_h^*}{N_h^*} \\ \frac{\beta_v S_v^*}{N_h^*} & \frac{\beta_v S_v^*}{N_h^*} & 0 \end{pmatrix}, \quad V = \begin{pmatrix} \gamma_h + \mu_h & 0 & 0 \\ 0 & \gamma_h + \mu_h & 0 \\ 0 & 0 & \mu_v \end{pmatrix}.$$

The next-generation matrix is $K = FV^{-1}$.

Computing $V^{-1} = \text{diag}((\gamma_h + \mu_h)^{-1}, (\gamma_h + \mu_h)^{-1}, \mu_v^{-1})$, we get

$$K = \begin{pmatrix} 0 & 0 & \frac{\theta \beta_h S_h^*}{N_h^* \mu_v} \\ 0 & 0 & (1 - \theta) \frac{\beta_h S_h^*}{N_h^* \mu_v} \\ \frac{\beta_v S_v^*}{N_h^* (\gamma_h + \mu_h)} & \frac{\beta_v S_v^*}{N_h^* (\gamma_h + \mu_h)} & 0 \end{pmatrix}$$

Let $\frac{\theta \beta_h S_h^*}{N_h^* \mu_v} = a$, $(1 - \theta) \frac{\beta_h S_h^*}{N_h^* \mu_v} = b$ and $\frac{\beta_v S_v^*}{N_h^* (\gamma_h + \mu_h)} = c$.

$$\text{Then } K = \begin{pmatrix} 0 & 0 & a \\ 0 & 0 & b \\ c & c & 0 \end{pmatrix}.$$

The characteristic polynomial of K can be computed as:

$$\det(K - \lambda I) = -\lambda^3 + \lambda c(a + b) = -\lambda(\lambda^2 - c(a + b)).$$

Thus, the eigenvalues are $\lambda = 0$ and $\lambda = \pm\sqrt{c(a+b)}$.

The spectral radius is $\rho(K) = \sqrt{c(a+b)}$.

Now, substituting the values of a, b, c and hence using values at DFE, we obtain the formula,

$$R_0 = \rho(FV^{-1}) = \frac{(1+\eta_1)\beta_{h0}(1+\eta_2)\beta_{v0}(1+\alpha)K_v\left(1-\frac{\mu_v}{(1+\eta_3)r_0}\right)}{\mu_v(\gamma_h+\mu_h)N_h^*} \quad (2.9)$$

Stability of Disease-Free Equilibrium

On the basis of the theory about the spectral radius of the next-generation matrix [15], we note the following. If $R_0 < 1$, then all eigenvalues of the linearization at E^* have negative real parts and hence E^* is locally asymptotically stable. If $R_0 > 1$, the linearization at E^* has an eigenvalue with positive real part since $R_0 - 1 = \rho(K) - 1 > 0$ gives a real positive root of the characteristic equation, hence E^* is unstable.

3. RESULTS AND DISCUSSION

3.1 Parameter Estimation and Model Calibration

To conduct numerical simulations and reproduce realistic dengue transmission dynamics, model parameters were estimated using a combination of methods:

Calculated Parameters: Demographic parameters such as human recruitment rate (Λ_h) and natural death rate (μ_h) were computed using census data (CBS, 2021) and the average life expectancy in Nepal.

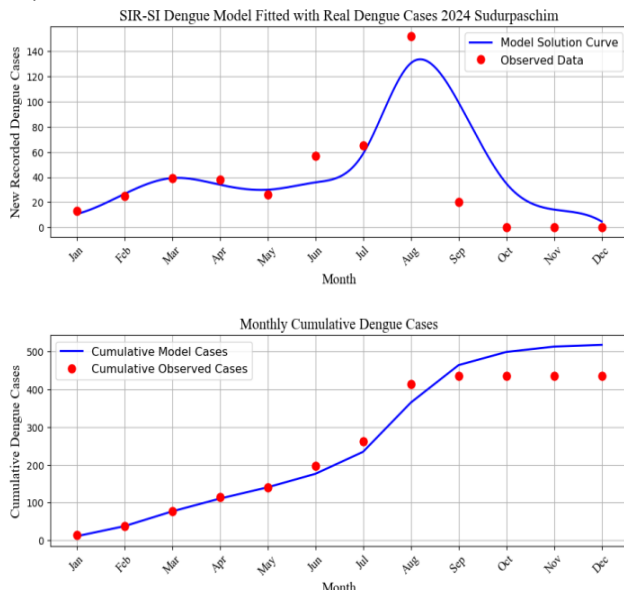


Fig. 4: Fitting the Dengue Model vs Real Time Dengue Data 2024 Sudurpashchim.

Data-Driven Fitting: Monthly new dengue cases of 2024 reported in Sudurpashchim Province was obtained from the Epidemiology and Disease Control Division (EDCD), Nepal. Parameters such as the transmission rate from vector to human (β_h) and human to vector (β_v), reporting proportion (θ), the vector carrying capacity K_v , mosquito death rate (μ_v), mosquito growth rate (r), and human recovery rate (γ_h) were calibrated by minimizing the sum of

squared errors between observed and predicted monthly new infections. Here, the initial intervals for values of the fitted parameters during optimization were assumed being based on ranges reported in peer-reviewed literature [4, 18, 19]. Reasonable ranges were selected to reflect the local climatic and epidemiological context of Nepal.

This parameter estimation process ensures the model captures key biological, epidemiological, and environmental factors influencing dengue dynamics in Sudurpashchim.

Table 1: Estimated Parameters: Source and description.

Parameter	Estimated Value	Source	Parameter	Estimated Value
Λ_h	130	calculated	r	1.4
μ_h	0.00119	calculated	K_v	4976640
β_h	2.79	data fitting	θ	0.11225
β_v	2.77	data fitting	α	2.81
γ_h	2.15827	data fitting	η_1, η_2, η_3	1.5
μ_v	1.80723	data fitting	R_0	1.9499

(Source: Data fitting)

3.2 Sensitivity Analysis

Each of the parameters $\eta_i = \eta, i = 1, 2, 3$ and α was varied from 75% to 150% of its baseline value. Plots were generated showing the sensitivity of R_0 with respect to key parameters α, γ_h, η and μ_v are presented in Fig. 5 (a). The resulting value of R_0 was computed and heatmap is plotted as shown in Fig. 5 (b).

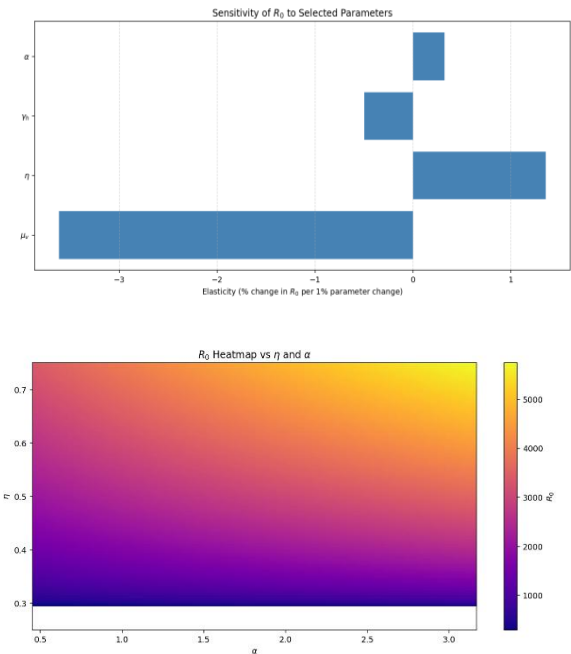


Fig. 5: Sensitivity analysis of the basic reproduction number and heat-map.

These results help to identify which parameters are critical for control strategies (e.g., vector control, sanitation, or public awareness). Sensitivity analysis supports the design of robust, data-informed intervention policies.

Fig. 5 illustrates the sensitivity of dengue outbreak dynamics to key model parameters: mosquito mortality rate (μ_v), initial susceptible

vector population (S_v^0), transmission rates β_h and β_v , and human recovery rate (γ_h). Each subplot reveals how changes in these parameters influence the total number of new dengue cases, peak infection size, and timing of the epidemic peak.

Increment in the mosquito mortality rate μ_v results in a significantly delayed and reduced epidemic peak. Even modest increments in μ_v lead to substantial reductions in disease burden, highlighting the critical role of adult mosquito control (e.g., safe use of insecticides, environmental management). This finding aligns with biological expectations, as higher mosquito death rates limit the infectious lifespan and overall vector population.

Similarly, reduction in the initial susceptible vector population S_v^0 —which can be interpreted as lowering the vector carrying capacity via reduced breeding sites (e.g., eliminating stagnant water, waste management)—also results in a notably lower and delayed peak. This supports the effectiveness of pre-monsoon vector source reduction programs in tropical regions like Sudur Pashchim, where vector populations rise with rainfall (Fig.6).

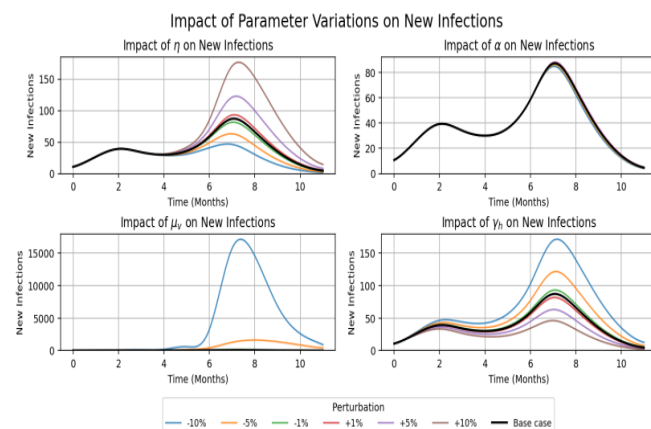


Fig. 6: Impact of some parameters in the peak time and size of infections.

Higher transmission rates β_h and β_v naturally increase the outbreak size and cause earlier peaks, underscoring the importance of reducing human-vector contact. Use of mosquito repellents, protective clothing, and awareness campaigns could help reduce effective transmission. In contrast, increasing the human recovery rate (γ_h) shortens infection duration and dampens the outbreak peak, though this may depend on treatment access and public health response.

4. CONCLUSION AND RECOMMENDATION

Mathematical model for dengue transmission dynamics is constructed, analyzed and fitted with monthly dengue cases of one year reported in Sudur Pashchim province of Nepal. Our model incorporates with the impacts of key climatic factors temperature and rainfall which are periodic in the region. Our model simply includes parameters for average increment in mosquito growth rate, transmission rates, mosquito mortality due to the warm temperature of summer period. Also, the average impact of rainy season over carrying capacity of environment for mosquito population is involved in the model. These parameters make the model more realistic than usual deterministic models employed in other studies in Nepal and better describing the seasonality of

dengue in the reasons like Nepal. The small reported proportion and only monthly data availability (not strong) are limitations of our study. If the data were a bit richer (e.g. weekly and well reported) and parameters were time dependent as temperature and rainfall (instead of the impacts in average) the model could do still better.

Based on the findings of our study, we recommend integrated vector management focusing on strategies.

Mosquito mortality increase: Promote safe insecticide use and larvicide treatment to moderately raise μ_v , which simulations show can significantly flatten and delay epidemic peaks.

Source reduction: Reduce S_v^0 by targeting breeding sites before and during monsoon, as this greatly lowers transmission potential.

Transmission reduction: Encourage personal protection measures to reduce β_h and β_v , especially during the summer and post-monsoon months.

Case management: Improve healthcare access and early diagnosis to increase γ_h , reducing infectious periods and secondary transmissions. These interventions, especially when coordinated and seasonally timed, could significantly mitigate dengue burden in Sudurpaschim and similar regions.

AUTHORS CONTRIBUTIONS

YR Pant: Conceptualization, model formulation, analysis, simulation; N Kharel: Conceptualization, model, analysis, simulation; A Bhatta: Mathematical analysis, data collection, data management, typing, simulation; P Chaudhary: Mathematical analysis, data collection, data management, typing, simulation.

ETHICAL ISSUES AND SAFETY

Since we have used only secondary data published/provided by authentic offices with provided proper citations, there is no ethical issues. Our data collection process does not affect public and species.

CONFLICT OF INTEREST

Authors declare that there are no conflicts of interest or competing financial interests to influence the work presented in this paper.

ACKNOWLEDGMENTS

Authors acknowledge Dr. Khagendra Adhikari, Lecturer, Tribhuvan University, Amrit Campus, Kathmandu, for his invaluable guidelines and suggestions.

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