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EVALUATING VECTOR AND HUMAN CONTROL STRATEGIES FOR DENGUE TRANSMISSION IN THE PHILIPPINES IN THE ABSENCE OF VACCINATION

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Abstract. Dengue remains one of the most critical public health challenges in the Philippines. In the absence of an effective vaccine, the most practical means of mitigating its spread involve reducing the mosquito population and minimizing human exposure to mosquito bites. This study introduces vector and human-based control strategies, with a particular emphasis on transmission reduction. A modified SIR dengue model, based on the work of de los Reyes and Escaner, is used to incorporate these interventions. Numerical simulations are conducted to evaluate the impact of the proposed controls when applied individually and in combination. The results show that sustained maximum control efforts throughout the year significantly reduce infection levels. Notably, the simultaneous implementation of both strategies at full intensity yields the most substantial decline in dengue cases. Additionally, the findings suggest that lower control weightings may be more effective in certain scenarios, offering a cost-efficient approach to outbreak management. These insights can aid public health authorities in designing more effective dengue prevention programs in the absence of vaccination.

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Key words and phrases. vector control; human control; dengue vaccine; optimal control; Pontryagin's Maximum Principle.

1. Introduction

Dengue fever is a mosquito-borne viral infection that poses a significant global health threat [9]. The virus is primarily transmitted to humans by infected female mosquitoes of the *Aedes aegypti* species, which serve as the primary urban vector of dengue worldwide [23,24]. There are four distinct serotypes of the dengue virus: DENV-1, DENV-2, DENV-3, and DENV-4, all capable of causing infection in humans [17]. Once a person is infected with one serotype, they acquire lifelong immunity to that specific serotype (homologous immunity), but only short-term immunity to the others (heterologous

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immunity), typically lasting around 12 weeks. After this period, they become susceptible again, with an increased risk of developing severe dengue or dengue hemorrhagic fever upon reinfection [18]. Dengue infection presents a wide spectrum of clinical manifestations, ranging from mild febrile illness to life-threatening complications due to capillary leakage [22]. Common symptoms include high fever, rash, severe headache, muscle and joint pain, and nausea, although a significant proportion of infected individuals remain asymptomatic [9].

In the Philippines, dengue continues to be a major public health concern, with widespread incidence across the country [2,7]. Among the 10 ASEAN member states, the Philippines ranks fourth in the number of reported dengue cases [14, 19, 21, 25]. As of October 4, 2024, the Department of Health (DOH) has reported 269,467 dengue cases—an alarming 82% increase from the 147,678 cases reported during the same period in the previous year [5]. In the absence of a widely accessible and effective vaccine, vector control remains one of the most practical and vital approaches for reducing dengue transmission. Vector control encompasses interventions aimed at limiting the mosquito population and their ability to transmit the virus [10]. However, its effectiveness is influenced by factors such as mosquito population density, human behavior, and environmental conditions [1].

Mathematical modeling, especially when integrated with optimal control theory, offers powerful tools for analyzing disease dynamics and identifying cost-effective, sustainable intervention strategies [12]. These models have been extensively used to better understand dengue transmission and to assess the potential impact of various control measures. Previous studies have shown that integrated strategies combining both vector and human behavioral controls can significantly reduce dengue incidence [6,20].

In this study, we revisit and extend the compartmental dengue transmission model developed by de los Reyes et al. by incorporating both vector and human control strategies. We evaluate two main categories of interventions: vector control strategies (e.g., mosquito population suppression) and human control strategies (e.g., minimizing mosquito-human contact). Since our focus is on non-vaccine approaches, vaccine-related interventions are excluded from this analysis. We apply optimal control theory to assess the effectiveness of these strategies in reducing dengue transmission in the absence of vaccination. Numerical simulations are conducted to explore the implications and potential outcomes of the enhanced model.

This research is particularly relevant in the context of the Philippines' ongoing struggle with dengue. The study's findings offer critical insights into the effectiveness of non-vaccine-based interventions and underscore the importance of integrated control strategies. By improving understanding of these approaches, this work contributes to more effective public health planning and enhances the country's capacity to manage dengue outbreaks, thereby strengthening the resilience of the national health system.

2. Optimal Control of the Epidemiological Model

Optimal control is a mathematical tool used in epidemiology to minimize disease spread while accounting for healthcare, economic, and social constraints. It determines the best control inputs that minimize a cost functional representing the total cost of managing the system over time. This section introduces optimal control measures focusing on mosquito population reduction and transmission reduction to manage dengue transmission more effectively. These control strategies are integrated into the dengue transmission model proposed by de los Reyes and Escaner [3]. The succeeding subsections provide a detailed analysis of the optimal control model, highlighting the main results. Finally, numerical simulations are presented to illustrate the impact of these control strategies on the model output, specifically the number of unhospitalized/unmonitored infectious humans (I_h), including a dedicated subsection exploring the effects of varying control weights.

To effectively prevent the spread of the dengue virus while minimizing associated costs, we propose the implementation of an optimal control strategy. Among the most effective interventions is the reduction of the mosquito population, which we introduce here as a vector control measure. This includes eliminating *Aedes aegypti* breeding sites, particularly water-holding containers that support larval development through actions such as regularly emptying and scrubbing water storage containers, cleaning gutters, properly disposing of discarded containers, and covering water storage units with tight-fitting lids or mesh screens. Additional measures involve the use of larvicides and adulticides, targeted insecticide spraying at breeding sites and surrounding areas, and fogging.

However, vector control alone is insufficient to eradicate dengue transmission. Therefore, we also propose a second control measure for the human population: transmission reduction control. The most effective defense against mosquito-borne diseases is preventing mosquito bites. This includes wearing loose-fitting, long-sleeved, light-colored clothing, as well as covered footwear and socks—especially during dawn and dusk when mosquitoes are most active—using mosquito repellents, and sleeping under insecticide-treated mosquito nets, among others.

To formalize these interventions, the epidemiological dengue model presented in [3] is reformulated as a control problem with the objective of minimizing the number of unhospitalized/unmonitored infectious humans, denoted by I_h. Let $u_v(t)$ represent the vector control intervention, which directly reduces the mosquito population and consequently affects both the susceptible (S_v) and infected (I_v) vector compartments. Similarly, let $u_h(t)$ denote the transmission reduction control, which decreases the rate at which mosquitoes transmit the virus to humans, thereby lowering the incidence of new infections. The state flow diagram illustrating the system dynamics under the influence of $u_v(t)$ and $u_h(t)$ is shown in Figure 1.

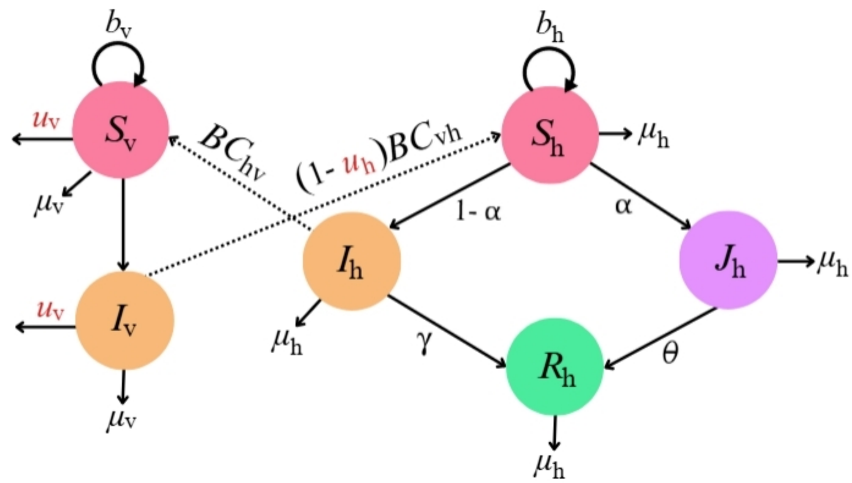


FIGURE 1. The state flow diagram of the system under the two control variables $u_v(t)$ and $u_h(t)$.

The following is the system of the controlled dengue model given in equations (2.1)–(2.2):

Vector Population:

$$\begin{aligned} \frac{dS_v}{dt} &= b_v N_v \left(1 - \frac{N_v}{K}\right) - \left(BC_{hv}\frac{I_h}{N_h} + \mu_v\right) S_v - u_v S_v, \\ \frac{dI_v}{dt} &= BC_{hv} S_v \frac{I_h}{N_h} - \mu_v I_v - u_v I_v \ . \end{aligned} \tag{2.1}$$

Human Population:

$$\begin{aligned} \frac{dS_h}{dt} &= b_h N_h - \left((1-u_h)BC_{vh}\frac{I_v}{N_h} + \mu_h\right) S_h, \\ \frac{dI_h}{dt} &= (1-\alpha)(1-u_h)BC_{vh}\frac{S_h I_v}{N_h} - (\gamma + \mu_h) I_h, \\ \frac{dJ_h}{dt} &= \alpha(1-u_h)BC_{vh} S_h \frac{I_v}{N_h} - (\theta + \mu_h) J_h, \\ \frac{dR_h}{dt} &= \gamma I_h + \theta J_h - \mu_h R_h \ , \end{aligned} \tag{2.2}$$

where $N_v = S_v + I_v$ and $N_h = S_h + I_h + J_h + R_h$. The two control inputs $u_v(t)$ and $u_h(t)$ are assumed to be piecewise continuous functions taking values in a positive bounded set $\mathcal{U} = [u_{\min}, u_{\max}]$. The objective functional is given by

$$\min J(u_v(t), u_h(t)) = \int_0^{t_f} \left[B_0 I_h(t) + \frac{1}{2}B_1 u_v^2(t) + \frac{1}{2}B_2 u_h^2(t)\right] dt \tag{2.3}$$

subject to the systems of differential equation in (2.1)−(2.2). The weight B_0 is a positive constant representing the weight of the cost of treatment of the model output, which is the unhospitalized/unmonitored infectious human (I_h). Meanwhile, the weight B_1 is a positive constant representing the cost of the vector control $u_v(t)$ and the weight B_2 is a positive constant representing the cost of the transmission reduction control $u_h(t)$. We now have the following results.

Theorem 2.1. *There exist optimal controls $u_v^*(t)$ and $u_h^*(t)$ such that*

$$J(u_v^*(t), u_h^*(t)) = \min_{\mathcal{U}} J(u_v(t), u_h(t)) \tag{2.4}$$

where

$$\mathcal{U} = \{u_v(t), u_h(t) \in L^{+\infty}(0, t_f) : \forall t \in [0, t_f], u_{\min} \leq u_v(t), u_h(t) \leq u_{\max}\}.$$

The parameters $u_{\min} = 0.05$ and $u_{\max} = 0.95$ are the upper and lower bounds of the controls, respectively.

Proof. In order to prove the theorem, it suffices to check the following properties:

(i) The corresponding set of controls and the state variables is nonempty.

(ii) The control set $\mathcal{U}$ is convex and closed.

(iii) The right-hand side of the state system in (2.1)−(2.2) is bounded by a linear function in the state and control variables.

(iv) The integrand of the objective functional in (2.3) is convex on $\mathcal{U}$.

(v) There exist nonnegative constants c_1, c_2 and $\rho > 1$ satisfying

$$L(I_h, u_v(t), u_h(t)) \geq c_2 + c_1(u_v^\rho(t) + u_h^\rho(t)) \tag{2.5}$$

where L is the Lagrangian for the optimal control problems in equations (2.1)−(2.2). By using an analogous proof as in the works of [8], the Lagrangian for the optimal control problems of the systems in (2.1)−(2.2) is given by

$$L(I_h, u_v(t), u_h(t)) = B_0 I_h + \frac{1}{2}B_1 u_v^2(t) + \frac{1}{2}B_2 u_h^2(t). \tag{2.6}$$

We now prove the theorem by checking the following conditions:

(i) Now consider the system,

$$\begin{aligned}
\frac{dS_v}{dt} &= \widetilde{F}_1(t, S_v, I_v, S_h, I_h, J_h, R_h), \\
\frac{dI_v}{dt} &= \widetilde{F}_2(t, S_v, I_v, S_h, I_h, J_h, R_h), \\
\frac{dS_h}{dt} &= \widetilde{F}_3(t, S_v, I_v, S_h, I_h, J_h, R_h), \\
\frac{dI_h}{dt} &= \widetilde{F}_4(t, S_v, I_v, S_h, I_h, J_h, R_h), \\
\frac{dJ_h}{dt} &= \widetilde{F}_5(t, S_v, I_v, S_h, I_h, J_h, R_h), \\
\frac{dR_h}{dt} &= \widetilde{F}_6(t, S_v, I_v, S_h, I_h, J_h, R_h),
\end{aligned} \tag{2.7}$$

where $\widetilde{F}_1$, $\widetilde{F}_2$, $\widetilde{F}_3$, $\widetilde{F}_4$, $\widetilde{F}_5$, and $\widetilde{F}_6$ represent the right-hand sides of system (2.1)−(2.2). The functions $\widetilde{F}_i$, for $i = 1, \ldots, 6$, are all linear, and their partial derivatives with respect to all state variables are constants. Hence, the functions and their partial derivatives are continuous everywhere. Thus, by the existence theorem [11,15], there exists a unique solution $S_v(t) = \varphi_1(t),\ I_v(t) = \varphi_2(t),\ S_h(t) = \varphi_3(t),\ I_h(t) = \varphi_4(t),\ J_h(t) = \varphi_5(t),\ R_h(t) = \varphi_6(t)$, which satisfies the initial conditions. Therefore, the corresponding set of controls and the state variables is nonempty.

(ii) The control set is convex and closed by conditon (i), hence giving condition (ii).

(iii) Note that the state system is linear in $u_v(t)$ and $u_h(t)$, therefore the right-hand side of the systems in (2.1)−(2.2) will satisfy condition (iii).

(iv) The control functional is convex in $\mathcal{U}$ since the solution to the systems of equations in (2.1)−(2.2) is closed and bounded by the condition (ii), hence giving condition (iv).

(v) Let $\bar{c_2} = I_h$ and let $c_1 = \min\,(B_1, B_2)$, $\rho = 2$. Then the Lagrangian L can be rewritten as

$$\begin{aligned} L(I_h, u_v(t), u_h(t)) &= B_0 I_h + \frac{1}{2} B_1 u_v^2(t) + \frac{1}{2} B_2 u_h^2(t) \\ &\geq B_0 \bar{c_2} + c_1(|u_v(t)|^2 + |u_h(t)|^2) \\ &= c_2 + c_1(u_v^2(t) + u_h^2(t)). \end{aligned}$$

Accordingly, there exists an optimal control for the systems of equations in (2.1)−(2.2) since all the conditions are satisfied.

□

Theorem 2.2. *The system of equations in* (2.1)−(2.2) *admits a unique optimal solution* $(S_v^*, I_v^*, S_h^*, I_h^*, J_h^*, R_h^*)$ *associated with optimal controls* $u_v^*(\cdot)$ *and* $u_h^*(\cdot)$ *on* $[0, t_f]$ *with a fixed final time* t_f*. Moreover, there exists adjoint functions* $\lambda_k^*(\cdot)$, $k = 1, \ldots, 6$ *satisfying*

$$\lambda_1' = -\lambda_1 \left(-\left(BC_{hv} \frac{I_h}{N_h} + \mu_v \right) - u_v \right) - \lambda_2 BC_{hv} \frac{I_h}{N_h}, \tag{2.8}$$

$$\begin{aligned} \lambda_2' = &-\lambda_2 \left(-(\mu_v + u_v) \right) - \lambda_3 \left(-(1-u_h) BC_{vh} \frac{S_h}{N_h} \right) \\ &- \lambda_4 \left(1 - \alpha(1-u_h) BC_{vh} \frac{S_h}{N_h} \right) - \lambda_5 \left(\alpha(1-u_h) BC_{vh} \frac{S_h}{N_h} \right), \end{aligned} \tag{2.9}$$

$$\begin{aligned} \lambda_3' = &-\lambda_3 \left(-(1-u_h) BC_{vh} \frac{I_v}{N_h} + \mu_h \right) - \lambda_4 \left(1 - \alpha(1-u_h) BC_{vh} \frac{I_v}{N_h} \right) \\ &- \lambda_5 \left(\alpha(1-u_h) BC_{vh} \frac{I_v}{N_h} \right), \end{aligned} \tag{2.10}$$

$$\lambda_4' = -B_0 - \lambda_1 \left(-BC_{hv} \frac{S_v}{N_h} \right) - \lambda_2 BC_{hv} \frac{S_v}{N_h} - \lambda_4(-(\gamma + \mu_h)) - \lambda_6 \gamma, \tag{2.11}$$

$$\lambda_5' = -\lambda_5(-(\theta + \mu_h)) - \lambda_6 \theta, \tag{2.12}$$

$$\lambda_6' = -\lambda_6(-\mu_h). \tag{2.13}$$

with the transversality conditions $\lambda_k^*(t_f) = 0$ for all $k = 1, \ldots, 6$. In addition, the optimal control variables are given by

$$u_v^*(t) = \max\left(\min\left(\frac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1}, u_v^{\max}(t)\right), 0\right),$$
$$u_h^*(t) = \max\left(\min\left(\frac{A}{B_2}, u_h^{\max}(t)\right), 0\right),$$

where

$$A = -\lambda_3 BC_{vh} S_h^* \frac{I_v^*}{N_h} + \lambda_4 (1-\alpha) BC_{vh} S_h^* \frac{I_v^*}{N_h} + \lambda_5 \alpha BC_{vh} S_h^* \frac{I_v^*}{N_h}.$$

Proof. Consider the following set of admissible control functions:

$$\mathcal{U} = \{u_v(t), u_h(t) \in L^{+\infty}(0, t_f) : \forall t \in [0, t_f], u_{\min} \le u_v(t), u_h(t) \le u_{\max}\}$$

where the parameters $u_{\min} = 0.05$ and $u_{\max} = 0.95$ are the upper and lower bounds of the controls. Since the integrand of the cost functional in (2.3) with respect to the controls $u_v(t)$ and $u_h(t)$ is convex by Theorem 2.1 and by the Lipschitz property of the state system with respect to state variables $(S_v, I_v, S_h, I_h, J_h, R_h)$, then the unique optimal solutions $(S_v^*, I_v^*, S_h^*, I_h^*, J_h^*, R_h^*)$ associated with optimal controls $u_v^*(\cdot)$ and $u_h^*(\cdot)$ on $[0, t_f]$ exist. The Hamiltonian for the optimal control in (2.3) is defined by

$$\begin{aligned}
H &= B_0 I_h + \frac{1}{2} B_1 u_v^2(t) + \frac{1}{2} B_2 u_h^2(t) \\
&\quad + \lambda_1 \left(b_v N_v \left(1 - \frac{N_v}{K}\right) - \left(BC_{hv} \frac{I_h}{N_h} + \mu_v\right) S_v - u_v S_v \right) \\
&\quad + \lambda_2 \left(BC_{hv} S_v \frac{I_h}{N_h} - \mu_v I_v - u_v I_v \right) \\
&\quad + \lambda_3 \left(b_h N_h - \left((1-u_h) BC_{vh} \frac{I_v}{N_h} + \mu_h \right) S_h \right) \\
&\quad + \lambda_4 \left((1-\alpha)(1-u_h) BC_{vh} \frac{S_h I_v}{N_h} - (\gamma + \mu_h) I_h \right) \\
&\quad + \lambda_5 \left(\alpha (1-u_h) BC_{vh} S_h \frac{I_v}{N_h} - (\theta + \mu_h) J_h \right) \\
&\quad + \lambda_6 \left(\gamma I_h + \theta J_h - \mu_h R_h \right).
\end{aligned}$$

The adjoint system is obtained by taking the negative of the partial derivative of the Hamiltonian H with respect to each state variables, that is,

$$\begin{aligned}
\lambda_1' &= -H_{S_v} = -\lambda_1 \left(-\left(BC_{hv} \frac{I_h}{N_h} + \mu_v \right) - u_v \right) - \lambda_2 BC_{hv} \frac{I_h}{N_h}, \\
\lambda_2' &= -H_{I_v} = -\lambda_2 \left(-(\mu_v + u_v) \right) - \lambda_3 \left(-(1-u_h) BC_{vh} \frac{S_h}{N_h} \right) \\
&\qquad - \lambda_4 \left(1 - \alpha (1-u_h) BC_{vh} \frac{S_h}{N_h} \right) - \lambda_5 \left(\alpha (1-u_h) BC_{vh} \frac{S_h}{N_h} \right), \\
\lambda_3' &= -H_{S_h} = -\lambda_3 \left(-(1-u_h) BC_{vh} \frac{I_v}{N_h} + \mu_h \right) - \lambda_4 \left(1 - \alpha (1-u_h) BC_{vh} \frac{I_v}{N_h} \right)
\end{aligned}$$

$$
\begin{aligned}
&\qquad - \lambda_5 \left(\alpha(1-u_h)BC_{vh}\frac{I_v}{N_h} \right), \\
\lambda_4' &= -H_{I_h} = -B_0 - \lambda_1 \left(-BC_{hv}\frac{S_v}{N_h} \right) - \lambda_2 BC_{hv}\frac{S_v}{N_h} - \lambda_4(-(\gamma+\mu_h)) - \lambda_6\gamma, \\
\lambda_5' &= -H_{J_h} = -\lambda_5(-(\theta+\mu_h)) - \lambda_6\theta, \\
\lambda_6' &= -H_{R_h} = -\lambda_6(-\mu_h).
\end{aligned}
$$

Optimal controls $u_v^*(t)$ and $u_h^*(t)$ are derived by taking the partial derivative of the Hamiltonian H with respect to the optimal controls and equating to zero. Then using the fact that $u_v(t) = u_v^*(t)$ and $u_h(t) = u_h^*(t)$, then we have

$$
\begin{aligned}
\frac{\partial H}{\partial u_v} &= -\lambda_1 S_v - \lambda_2 I_v + B_1 u_v \\
0 &= -\lambda_1 S_v - \lambda_2 I_v + B_1 u_v \\
B_1 u_v &= \lambda_1 S_v + \lambda_2 I_v \\
u_v^* &= \frac{\lambda_1 S_v + \lambda_2 I_v}{B_1},
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial H}{\partial u_h} &= \lambda_3 BC_{vh}S_h\frac{I_v}{N_h} - \lambda_4(1-\alpha)BC_{vh}S_h\frac{I_v}{N_h} - \lambda_5\alpha BC_{vh}S_h\frac{I_v}{N_h} + B_2 u_h \\
0 &= \lambda_3 BC_{vh}S_h\frac{I_v}{N_h} - \lambda_4(1-\alpha)BC_{vh}S_h\frac{I_v}{N_h} - \lambda_5\alpha BC_{vh}S_h\frac{I_v}{N_h} + B_2 u_h \\
B_2 u_h &= -\lambda_3 BC_{vh}S_h\frac{I_v}{N_h} + \lambda_4(1-\alpha)BC_{vh}S_h\frac{I_v}{N_h} + \lambda_5\alpha BC_{vh}S_h\frac{I_v}{N_h} \\
u_h^* &= \frac{-\lambda_3 BC_{vh}S_h\frac{I_v}{N_h} + \lambda_4(1-\alpha)BC_{vh}S_h\frac{I_v}{N_h} + \lambda_5\alpha BC_{vh}S_h\frac{I_v}{N_h}}{B_2}.
\end{aligned}
$$

Taking into account the bounds on the controls, then we have

$$
\begin{aligned}
u_v^*(t) &= \max\left(\min\left(\frac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1}, u_v^{\max}(t) \right), 0 \right), \\
u_h^*(t) &= \max\left(\min\left(\frac{A}{B_2}, u_h^{\max}(t) \right), 0 \right),
\end{aligned}
$$

where

$$
A = -\lambda_3 BC_{vh}S_h^*\frac{I_v^*}{N_h} + \lambda_4(1-\alpha)BC_{vh}S_h^*\frac{I_v^*}{N_h} + \lambda_5\alpha BC_{vh}S_h^*\frac{I_v^*}{N_h}.
$$

Applying the property of the control set, we have

$$
u_v^*(t) = \begin{cases}
0, & \text{if } \dfrac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1} \le 0, \\[2ex]
\dfrac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1}, & \text{if } \dfrac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1} < u_v^{\max}(t), \\[2ex]
u_v^{\max}(t), & \text{if } \dfrac{\lambda_1 S_v^* + \lambda_2 I_v^*}{B_1} \ge u_v^{\max}(t),
\end{cases}
$$

$$u_h^*(t) = \begin{cases} 0, & \text{if} \quad \dfrac{A}{B_2} \leq 0, \\ \dfrac{A}{B_2}, & \text{if} \quad \dfrac{A}{B_2} < u_v^{\max}(t), \\ u_v^{\max}(t), & \text{if} \quad \dfrac{A}{B_2} \geq u_v^{\max}(t). \end{cases}$$

$\square$

3. Results and Discussions

In this section, we present the numerical analysis of the two optimal control strategies aimed at reducing dengue outbreaks. The optimality system in (2.1)−(2.2) is solved using the forward Runge–Kutta method with predefined initial conditions, while the adjoint system is solved using the backward sweep method with transversality conditions. The parameter values and initial conditions used are taken from [3] and are detailed in Table 1 and Table 2.

Parameter	**Description**	**Value**	**References**
b_h	Birth rate of humans	0.00085	[3]
μ_h	Mortality rate of humans	0.00045	[3]
B	Vector biting rate	1	[4]
C_{hv}	Transmission probability from human to vector	0.75	[4]
C_{vh}	Transmission probability from vector to human	0.375	[4]
γ	Non-seeking healthcare recovery rate	0.5	[13]
θ	Healthcare-seeking recovery rate	1	[13]
b_v	Per capita oviposition rate	75	[13]
μ_v	Mortality rate of vectors	0.1	[13]
K	Vector carrying capacity	3×10^8	Estimated
α	Transition rate from infected to hospitalized humans	0.2	Estimated

Table 1. Parameter values used in de los Reyes and Escaner dengue transmission model [3].

Parameter	**Description**	**Value**
$S_v(0)$	Initial condition for susceptible mosquitoes	20,000,000
$I_v(0)$	Initial condition for infected mosquitoes	2,000,000
$S_h(0)$	Initial condition for susceptible humans	50,000,000
$I_h(0)$	Initial condition for infected humans	15,000
$J_h(0)$	Initial condition for healthcare-seeking humans	1500
$R_h(0)$	Initial condition for recovered humans	5000

Table 2. Initial conditions used in de los Reyes and Escaner dengue transmission model [3].

The time t_f used for all simulations is fixed to 1 year (52 weeks) which is around the average infection season duration [16]. The values of the control weights B_0, B_1 and B_2 are all set to 1×10^{16}. The following intervention scenarios are considered:

Scenario 1: Vector control only

The optimal control strategy obtained for this scenario and its corresponding projected trend in the number of unhospitalized/unmonitored infectious humans over a one-year period are shown in Figure 2. The left panel illustrates that the vector control measure $u_v(t)$, is applied at its maximum intensity from the onset and remains at this level throughout the entire 52-week period. This suggests that maintaining a continuous, high-intensity vector control effort is crucial for effectively suppressing the mosquito population.

The right panel depicts the impact of this sustained vector control on the number of unhospitalized/unmonitored infectious individuals. Despite the early implementation of control measures, the number of infections initially increases rapidly before gradually declining. This initial surge is expected, as immediate elimination of all infectious vectors is unfeasible; thus, new cases continue to arise during the early stages of intervention. However, as the vector control remains at its peak intensity, a steady decline in infections follows, culminating in a substantially lower infection peak compared to the uncontrolled scenario. This outcome highlights the effectiveness of a consistently enforced vector control strategy in mitigating the severity of the outbreak and reducing its duration.

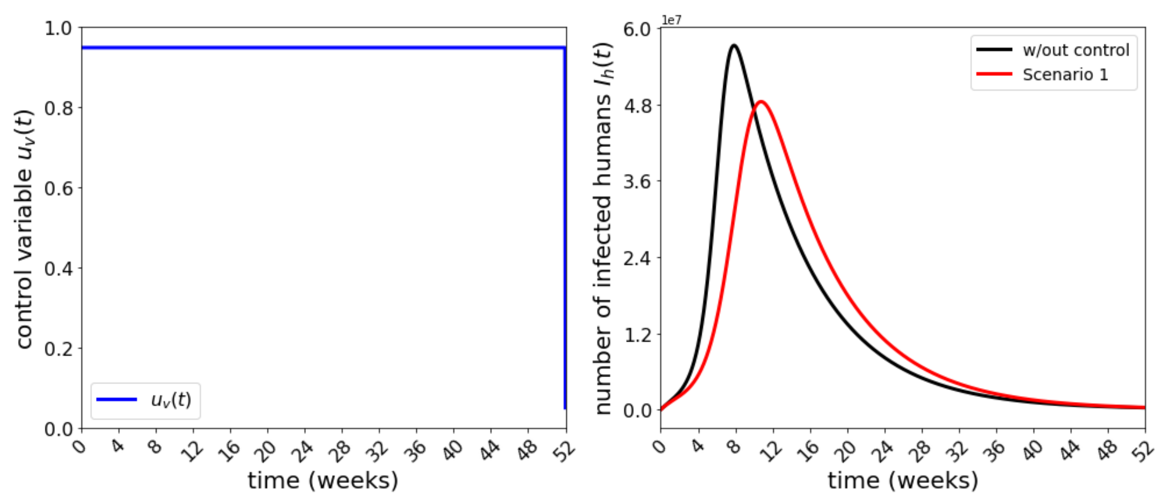


FIGURE 2. The optimal vector control strategy and its corresponding projected trend for the number of infected humans for Scenario 1.

Scenario 2: Transmission reduction control only

The optimal control strategy for this scenario, along with its projected impact on the number of unhospitalized/unmonitored infectious individuals over a one-year period, is illustrated in Figure 3. The left panel shows that the transmission reduction control $u_h(t)$ is applied at maximum intensity from the outset and maintained throughout the 52-week period. This indicates a sustained and rigorous implementation of the intervention across the year.

In the right panel, the infection curve exhibits a slower rise and delayed peak compared to Scenario 1, where infections surge rapidly. This more gradual progression suggests that infections in this scenario develop over time, likely due to the effects of the control measure. Although the control does not entirely prevent infections, it delays transmission—potentially because individuals are initially protected but may still become infected days or weeks later. This phenomenon can also be explained by the epidemiological concept of the latent period, which is the time between exposure to the virus and the onset of infectiousness. The presence of a latent period inherently slows the spread of the disease. Despite the continued transmission, a notable decline in the number of infected individuals is observed, with a delayed reduction compared to the uncontrolled scenario. This demonstrates that the transmission reduction control effectively suppresses the spread of dengue and plays a vital role in reducing the overall burden of infection, outperforming the results observed in Scenario 1.

Scenario 3: Coupled control strategy

Figure 4 presents the optimal coupled control strategy alongside its projected impact on the population of unhospitalized/unmonitored infectious individuals over a one-year period. The right panel distinctly illustrates that the most substantial reduction in infections is achieved when both control measures, vector control $u_v(t)$ and transmission reduction control $u_h(t)$, are implemented simultaneously. Under this combined strategy, the number of infected individuals declines to near-zero levels, substantially outperforming the outcomes of single-control scenarios. This finding highlights the superior effectiveness of the coupled control approach in mitigating disease spread.

Correspondingly, the left panel shows that both controls, $u_v(t)$ and $u_h(t)$, begin at their maximum levels and maintain this intensity throughout the entire year. This emphasizes the critical importance of sustained and aggressive intervention to effectively suppress dengue transmission and potentially eliminate the disease.

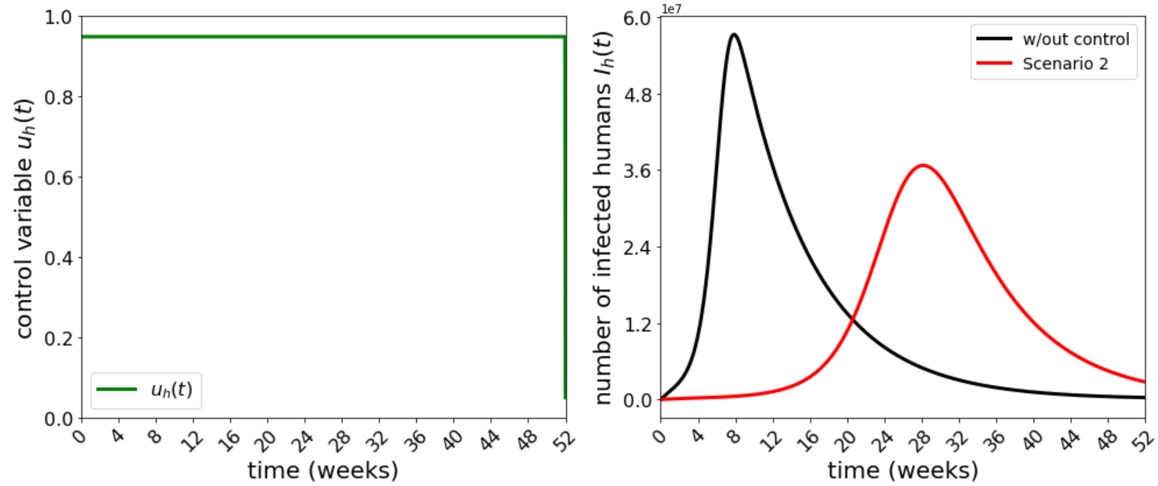


FIGURE 3. The optimal transmission reduction control strategy and its corresponding projected trend for the number of infected humans for Scenario 2.

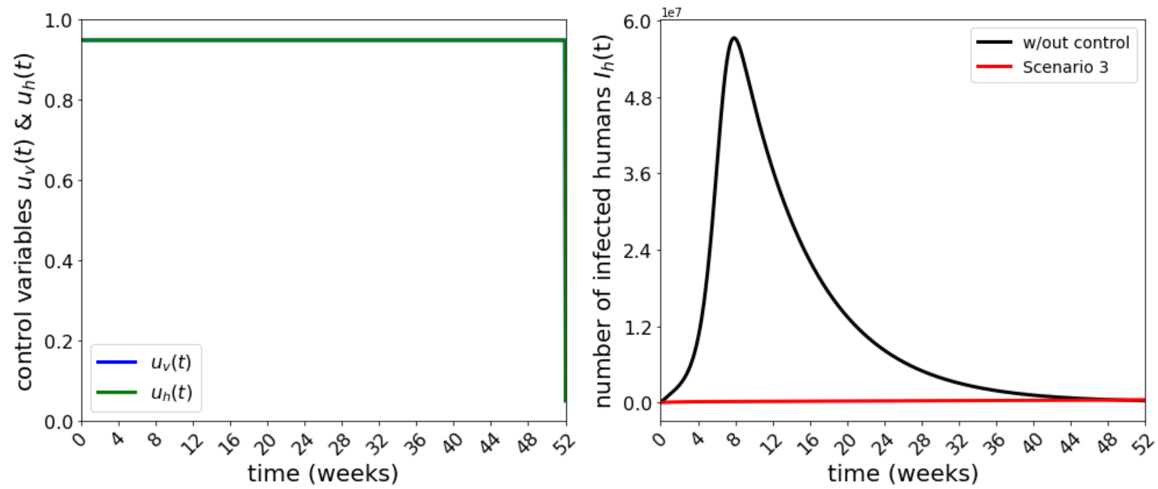


FIGURE 4. The optimal coupled control strategy and the corresponding projected trends for the number of infected humans for Scenario 3.

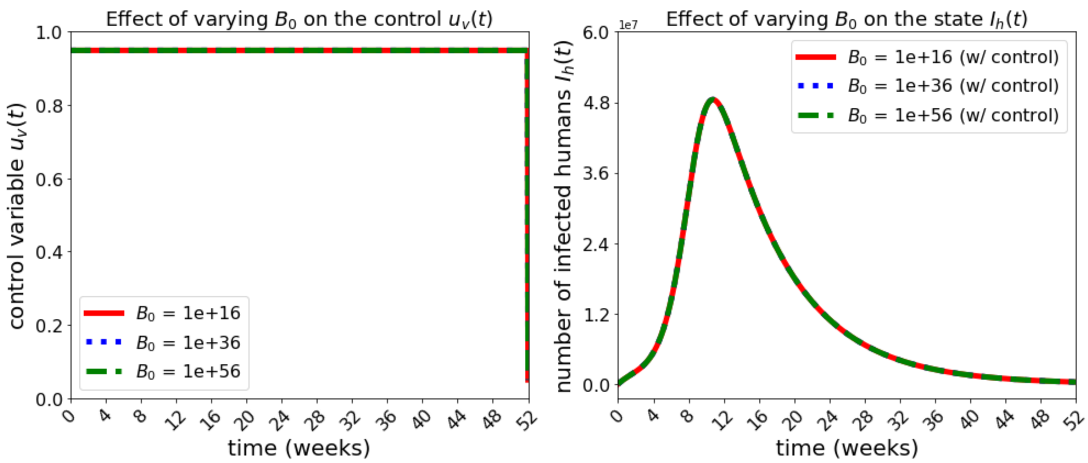
We will now investigate the responses of the controlled system with respect to the respective weight changes in the objective functional. To this end, the parameter B_0 which is associated with the unhospitalized/unmonitored infectious population, is firstly investigated. Define $B_0 = [1 \times 10^{16}, 1 \times 10^{36}, 1 \times 10^{56}]$ while fixing the weights B_1 and B_2 at 1×10^{16} for all simulations.

Figure 5 (a)$-$(c) illustrate the effects of varying the weight parameter B_0 on the control variables $u_v(t)$, $u_h(t)$, the coupled control, and the state variable $I_h(t)$. The left panels show that the controls $u_v(t)$, $u_h(t)$, and their combination remain at their maximum allowable levels throughout the 52-week intervention period, regardless of the increase in B_0. This behavior is expected, as B_0 corresponds to the cost associated with treating human infectives and does not directly influence the implementation of the vector control $u_v(t)$, the transmission reduction control $u_h(t)$, or their combined application. Consequently, the variation in B_0 has little to no effect on the control strategies, and its role in mitigating the spread of infection is less significant compared to the control efforts themselves. This is reflected in the right panels of the figure, where the trajectories of $I_h(t)$ remain virtually unchanged and closely follow those observed in Scenarios 1, 2, and 3.

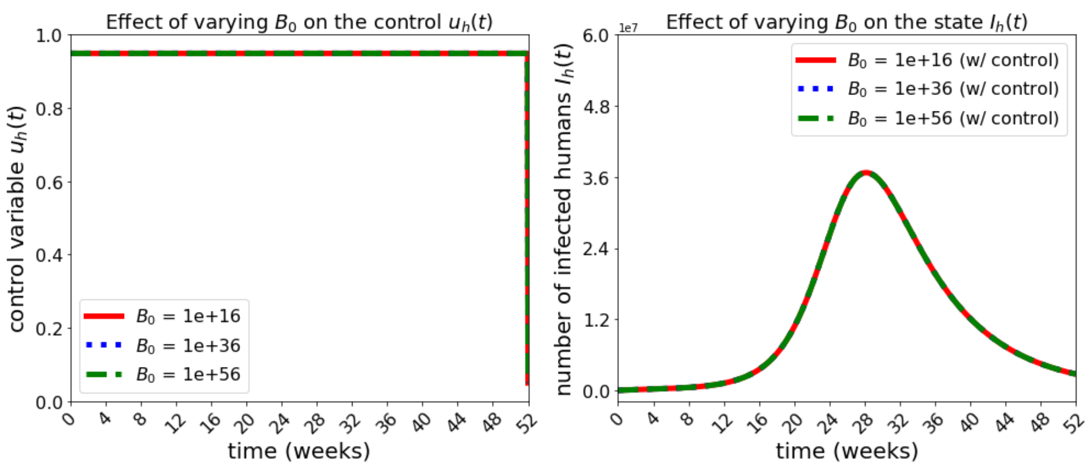
Next, we examine how the controlled system responds to variations in the control weight B_1. Specifically, we set $B_1 = [1 \times 10^{16}, 1 \times 10^{36}, 1 \times 10^{56}]$, while keeping the weights B_0 and B_2 fixed at 1×10^{16} across all simulations. Figure 6 (a)$-$(c) illustrates the influence of increasing B_1 on the control variables $u_v(t)$, $u_h(t)$, the coupled control, and the state variable $I_h(t)$. The left panels of Figures 6 (a) and (c) reveal a noticeable reduction in the vector control $u_v(t)$ and the coupled control as B_1 increases. In contrast, the left panel of Figure 6 (b) shows minimal changes in the human control $u_h(t)$, indicating a lesser sensitivity to variations in B_1. On the other hand, the right panels of Figures 6 (a) and (c) demonstrate that the number of human infectives $I_h(t)$ increases with higher values of B_1. These findings suggest that lower values of the control weight B_1 lead to more aggressive initial application of $u_v(t)$ and the coupled controls, which in turn help suppress the infectious population more effectively in Scenarios 1 and 3. Therefore, selecting a lower B_1 is advisable to reduce both the peak infection levels and the required control effort, thereby enhancing the effectiveness of dengue outbreak mitigation strategies in these scenarios.

Lastly, we examine the response of the controlled system to variations in the control weight B_2, while keeping B_0 and B_1 fixed at 1×10^{16} for all simulations. We consider three values of $B_2 = [1 \times 10^{16}, 1 \times 10^{26}, 1 \times 10^{36}]$. Figure 7 (a)$-$(c) illustrates the effects of increasing B_2 on the control variables $u_v(t)$, $u_h(t)$, the coupled control, and the state variable $I_h(t)$. Figure 7 (a) shows that changes in B_2 have little to no effect on the vector control $u_v(t)$, as this control is not directly influenced by B_2. The vector control effort remains at its maximum throughout the year, and the infection curves are largely unaffected.

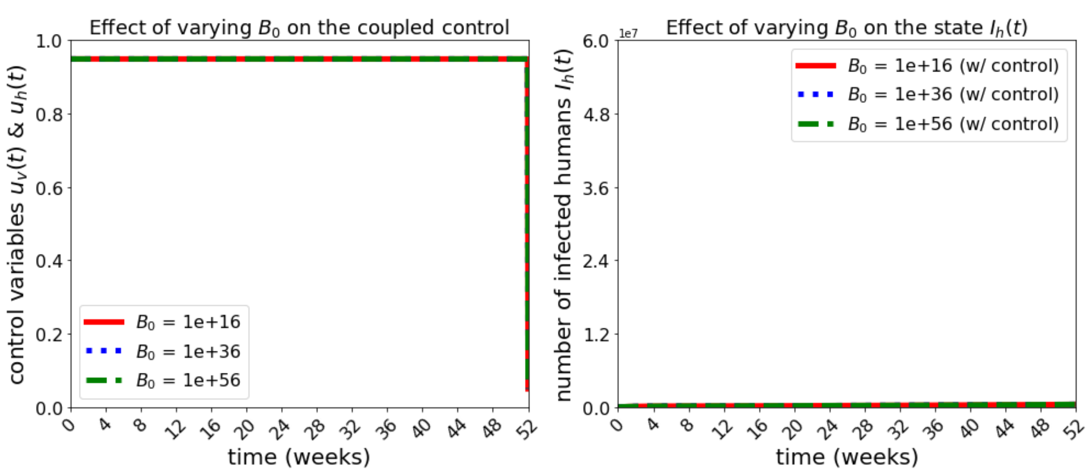
In contrast, Figures 7 (b) and (c) reveal a noticeable decrease in both the human-targeted control $u_h(t)$ and the coupled control as B_2 increases. Simultaneously, these figures show a corresponding increase in the number of human infectives $I_h(t)$. This increase is slight in Scenario 2 but more pronounced in Scenario 3. These observations suggest that higher values of B_2 discourage the use of $u_h(t)$, leading to earlier suspension of the control and, consequently, higher infection levels. Overall, the results indicate that lower values of B_2 encourage stronger initial deployment of $u_h(t)$ and the coupled control in Scenarios 2 and 3, respectively. Therefore, a lower weighting for B_2 is recommended to achieve more effective control of dengue transmission in these scenarios.



(A)

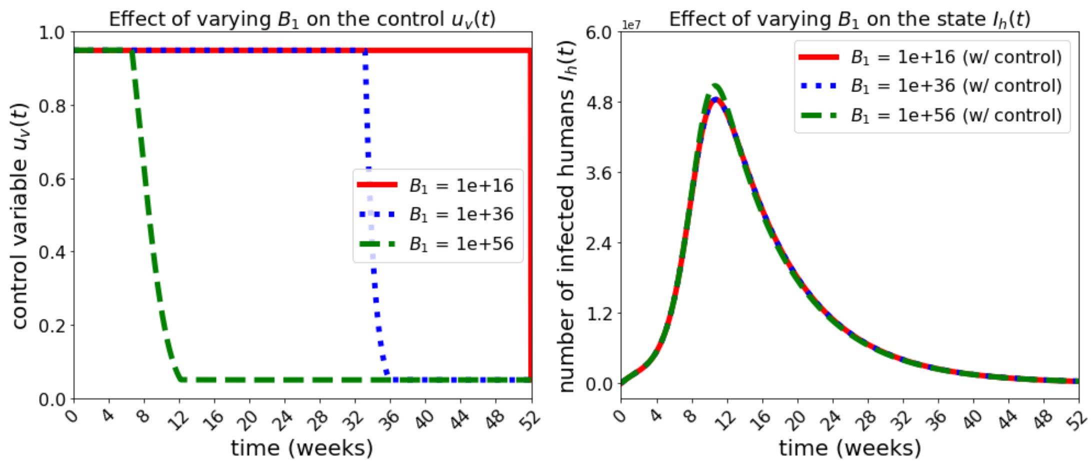


(B)

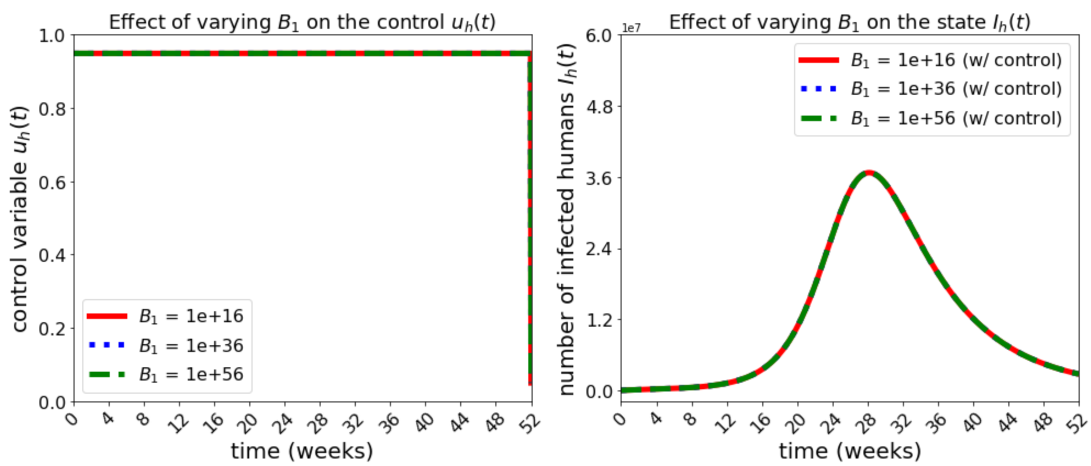


(C)

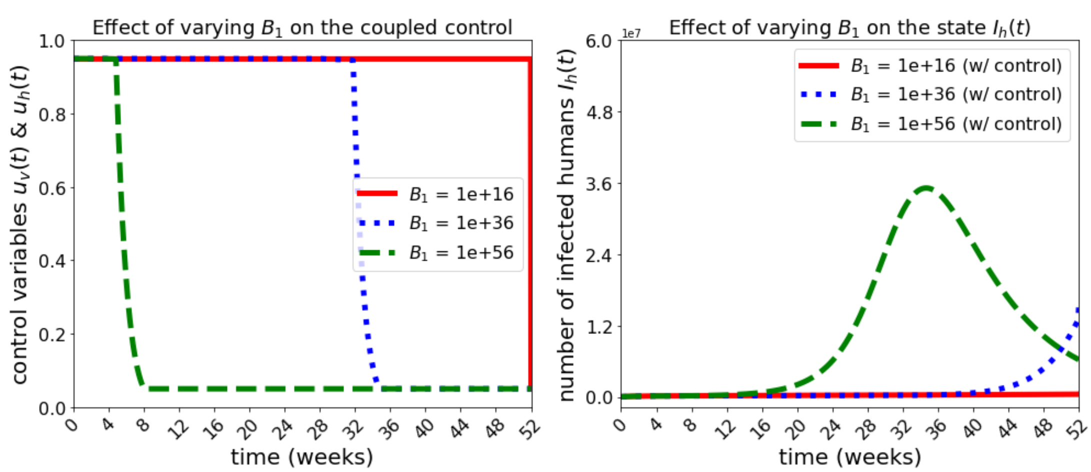
FIGURE 5. Effect of varying the control weight B_0 for the control variables $u_v(t)$, $u_h(t)$, coupled control, and state variable $I_h(t)$ for (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.



(A)

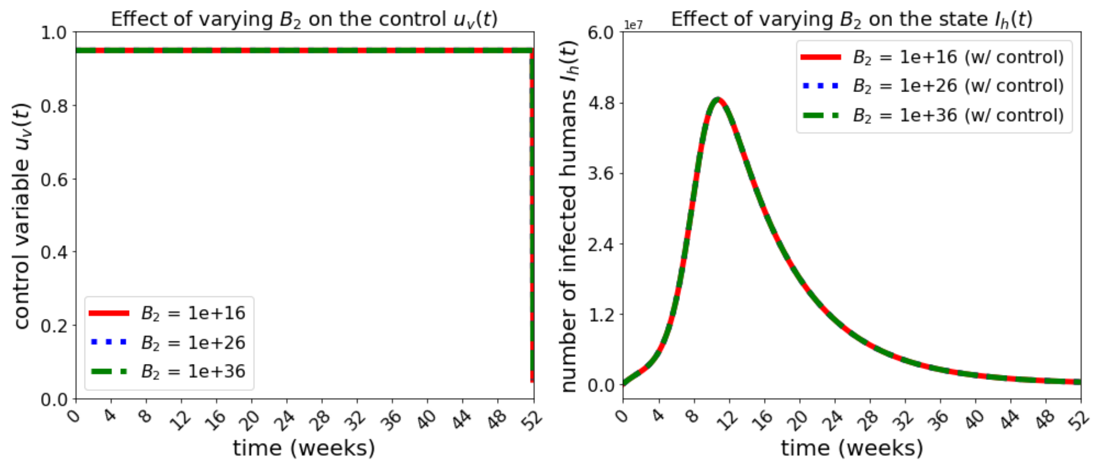


(B)

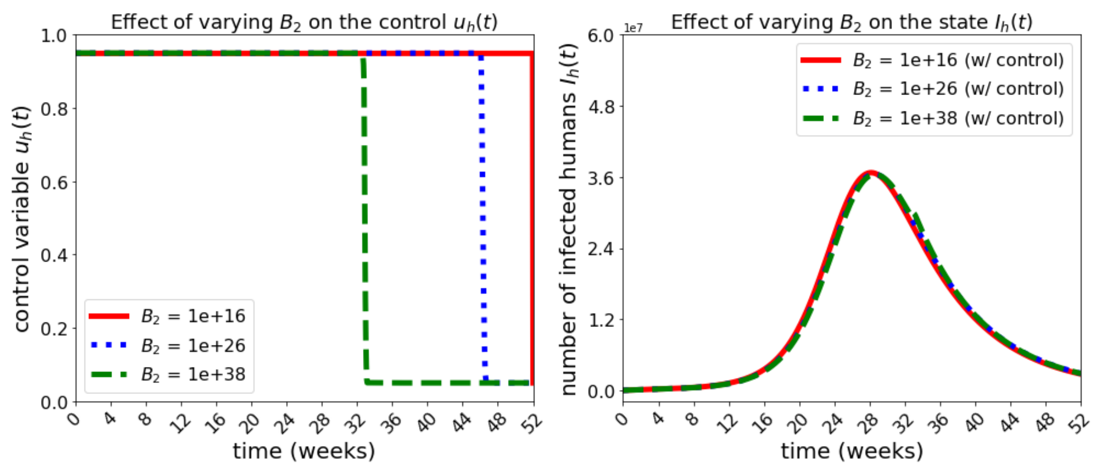


(C)

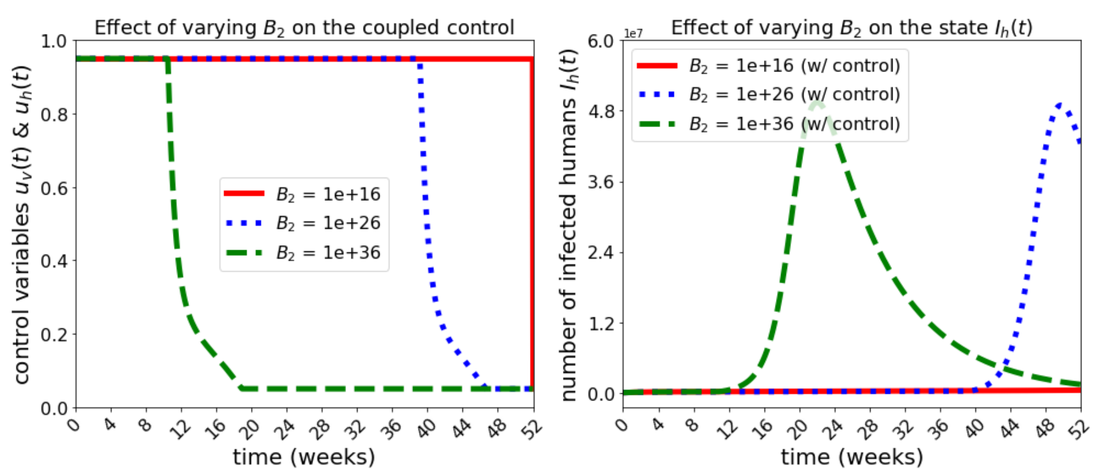
FIGURE 6. Effect of varying the control weight B_1 for the control variables $u_v(t)$, $u_h(t)$, coupled control, and state variable $I_h(t)$ for (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.



(A)



(B)



(C)

FIGURE 7. Effect of varying the control weight B_2 for the control variables $u_v(t)$, $u_h(t)$, coupled control, and state variable $I_h(t)$ for (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.

4. Conclusion

This study formulated an optimal control problem aimed at minimizing the number of unhospitalized or unmonitored human infectives by modifying the mathematical model of dengue transmission developed by de los Reyes and Escaner [3], under the assumption that no dengue vaccine is available. Two control strategies were considered: vector control, targeting the mosquito population, and transmission reduction control, aimed at the human population. The optimal control problem was explored under three distinct scenarios: Scenario 1 for vector control only, Scenario 2 for transmission reduction only, and Scenario 3 for a combination of both strategies. Pontryagin's Maximum Principle was employed to derive the necessary conditions for optimality. The resulting optimality system was solved using a forward Runge–Kutta method with predefined initial conditions, while the associated adjoint system was solved using the backward sweep method under specified transversality conditions.

Numerical simulations were conducted for each scenario. Results showed that applying maximum control efforts consistently throughout the year significantly reduces the number of infections. Among the strategies, the combined implementation of both controls (Scenario 3) at full intensity yielded the most effective results. Additionally, the impact of varying the weight parameters B_0, B_1 and B_2 was investigated. It was found that increasing B_0 had minimal effect on both the control efforts and the infection dynamics across all scenarios. In contrast, reducing B_1 was shown to lower the endemic infection levels and decrease the required control intensity for Scenarios 1 and 3. Similarly, reducing B_2 was beneficial for controlling outbreaks in Scenarios 2 and 3.

Implementing effective dengue control strategies requires appropriate budget allocation. Identifying the most cost-efficient measures can guide policy-makers in prioritizing funding toward the most impactful interventions. Therefore, the findings of this study offer valuable insights for public health authorities in designing cost-effective and efficient dengue prevention programs, particularly in contexts where vaccines are not yet available. Future work may extend this model by incorporating the availability of dengue vaccines and exploring their integration with the existing vector and transmission reduction controls. Such an approach can help determine the most effective combination of interventions to mitigate the spread of dengue in a cost-efficient manner.

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Conflicts of Interest. The authors declare that there are no conflicts of interest regarding the publication of this paper.

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