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ORIGINAL ARTICLE

Impact of social awareness, case detection, and hospital capacity on dengue eradication in Jakarta: A mathematical model approach☆

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Abstract Fumigation is the most popular form of intervention in various parts of the world to combat the spread of dengue fever, including in the city of Jakarta, Indonesia. Various forms of intervention, such as media campaign and case detection, are being carried out to control dengue in Jakarta. This study aims to understand the impact of the media campaign and case detection in controlling dengue spread in the city of Jakarta via a novel mathematical model. The intervention of a media campaign can improve people's knowledge of dengue, which can make them aware of dengue. Furthermore, we also define our recovery rate as a decreasing function depending on the number of hospitalized individuals. The model was developed as a novel SAEIHR-VW (Susceptible Aware Exposed Infected Hospitalized Recovered - Susceptible and Infected Mosquito) model. Incidence data in Jakarta during 2020 is used to estimate the best-fit parameter of the model. The analysis shows that the disease-free equilibrium is locally asymptotically stable when the basic reproduction number is less than one. The elasticity analysis demonstrates that media campaign intervention is much more sensitive than case detection in suppressing the basic reproduction number. Furthermore, larger case detection does not always provide a better result in reducing the basic reproduction number owing to the quality of treatment in the hospital. The dynamical system sensitivity analysis (local and global) shows that the infection probability rate is the most significant parameter for the infected and hospitalized individuals.

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1. Introduction

Dengue fever is an infectious disease that is transmitted through an intermediate vector of mosquitoes, namely the female Aedes mosquito. It has become a seasonal disease in many tropical countries, one of which is Indonesia, and continues to attract the attention of policymakers every year.

Dengue fever is caused by one of the five types of DEN-virus serotype [1]. Symptoms caused by this disease are very diverse, ranging from mild symptoms such as fever and headache (Dengue Fever/DF), severe symptoms (Dengue Hemorrhagic Fever/DHF) to those that can lead to death (Dengue Shock Syndrome/DSS) [2]. Because it was discovered for the first time in the 1950s [3] and studied in 1943 [4]. It has spread rapidly to all parts of the world (mainly tropical and subtropical countries) through urbanization, international travel, etc. and threatens one-third of the world's population every year.

Until now, no specific drug has been found that can cure patients who have been infected with dengue fever. The treatment provided in hospitals focuses on the symptoms that arise to prevent the patient's condition from worsening. If the patient's symptoms are still relatively mild, then adequate rest is the recommended action for the patient. However, if indications of a low pulse, low urine output extends to a rising hematocrit ($\geqslant 20\%$), or falling platelet count ($> 100000/mm^3$) appears, the patient is to immediately seek intensive care at the hospital [5]. The problem is when the number of dengue fever cases is very high, the services at the hospital struggle to function become increasingly difficult to function optimally owing to the limited facilities in the hospital.

Dengue in Indonesia and Jakarta. Ministry of Health data from 2021 shows 73,518 DBD cases in Indonesia. This is a 32.12% reduction from the previous year's total of 108,393. As of the 22nd week of 2022, The ministry of Health of Indonesia has recorded an increase of the number of yearly cases to 45,387. This increase mainly occurred during the rainy season, with a death toll of 432 [6]. According to the Directorate of Infectious Disease Control and Prevention (P2PM), from January 2022 to the 36th week of 2022, the total number of confirmed cases is 87,501, with 816 deaths. The highest number of cases is found in the 14–44 age group (accounting for 38.96% of cases), followed by the 5–14 age group (35.61% of cases) [7]. Although dengue is an annual disease, the number of cases often begins to increase in January, before peaking from March to April [8]. The highest incidence rate in Indonesia was found in 10 provinces: Bali, North Kalimantan, Bangka Belitung, East Borneo, East Nusa Tenggara, Jakarta, West Java, North Sulawesi, West Nusa Tenggara, and Yogyakarta [6]. Jakarta is the capital city of Indonesia, with a population of more than ten million people, with 14.09% of them having daily high mobility activities. This is the cause of the high number of dengue cases in Jakarta compared to other areas, and it is easy for dengue to spread geographically in Jakarta. Fig. 1 shows the incidence rate of dengue cases in Jakarta compared to the data from Indonesia from 2010 to 2014. It is observed that the incidence rate in Jakarta is always higher than that of Indonesia every year. This illustrates how dengue has received considerable attention from policymakers in Jakarta.

Many mathematical models that have been introduced to understand how dengue spreads depend on several important factors. Because dengue is caused by more than one type of DEN-virus serotype, the chances of infection by different viruses are very high. A person has a long life of immunity to the strain of the virus that first infects him; however, there is no immunity to the other strains. There is a temporal cross-immunity against other strains for a relatively short time [10]. Furthermore, this secondary infection can lead to death of the patient [11]. Earlier studies on two strain mathematical models for dengue was introduced by Esteva and Vargaz in 2003 [12]. On the contrary, Aguiar et al. introduced a more complex model on multiple dengue strain viruses and showed a possible chaotic behavior through their proposed model [13]. A more recent study on cross-immunity and multiple strains on the dengue model can be observed in [14]. Another essential factor in dengue transmission is the seasonal factor. There have been many studies that support the statement that dengue cases are closely related to the climate factor [15]. Chen and Hsieh [16] proposed a mathematical model on dengue transmission by considering temperature effects. They found that a higher transmission of dengue occurred when the temperature was equal to $28^\circ C$. Robert *et al.* [17] found that climate changes would likely increase the suitability of dengue transmission, and they used data from the United States for the study. Jayaraj *et al.* [18] proposed a predictive dengue model based on climate data in Tawau, Malaysia. As previously mentioned, the spreader of the dengue disease is the female Aedes type mosquito. This mosquito is also an intermediate vector that spreads Zika disease. Therefore, the possibility of co-infection between these two types of diseases in the human body is possible as discussed by [19]. In addition, another form of co-infection of dengue is with COVID-19. Rehman *et al.* [20] proposed their mathematical model to understand co-infection between dengue and COVID-19 in a complex network. Furthermore, Glover and White [21] proposed a model for co-infection between yellow fever and dengue. A Hopf bifurcation and global dynamics analysis on a time delayed dengue transmission model discussed by authors in [22]. They found that their model can go through Hopf bifurcation when the temporal delay is larger than the specific threshold. Recently, the author in [23] introduced a fractional model for dengue transmission. They considered vaccination, treatment, and reinfection in their model. Mathematical models on dengue control program are also considered by many authors to help the impact of possible strategies, such as vaccine only [24], vaccine combined with Wolbachia [25,26], vaccine considering multi-strain infection [27], fumigation/vector control [1], Wolbachia intervention [28], case finding [29], mosquitoes repellents [30], etc. In many circumstances, a mathematical model needs to be constructed to understand what the disease incidence data provides. Hence, testing the proposed model with the existing incidence data is a common means for authors achieve this. Many mathematical models have been tested by using dengue incidence data from many areas such as from India [29], Kupang, Indonesia [24], Semarang, Indonesia [31], or from China [32]. There are a few mathematical models proposed to understand dengue incidence in Jakarta. Wijaya et al. [33] proposed a seasonal effect on their model to understand the seasonality of dengue incidence in Jakarta. They found that Jakarta experienced a dengue outbreak every year. A different approach was used by Fakhruddin *et al.* [34] to understand the impact of the weather on dengue incidence in Jakarta, where they used a clustering inte-

Fig. 1 Comparison of the incidence rate in Indonesia and Jakarta (2010–2014) [9].

grated multiple regression model. A support vector machine was used by Tanawi *et al.* [35] to predict dengue incidence in Jakarta.

The literature shows that none of the mathematical models consider hospital capacity. Considering an endemic area, hospital capacity is always a problem during an outbreak. Comparatively, the hospital bed ratio per 1 000 individuals in Indonesia for 2017 was 1.04 [36]. This indicates that there are approximately 11 000 hospital beds available for approximately 11 million people in Jakarta. Moreover, the hospital bed ratio in Indonesia is problematic compared to that of the United States (2.3), China (4.3), or Japan (13.0). Hence, it is essential to include hospital capacity in our model, and this may affect the recovery rate of hospitalized individuals. Another crucial factor is about human awareness of the danger of dengue. Because no drug has yet been discovered to cure infected individuals, non-pharmaceutical intervention has become an options in the city of Jakarta. Therefore, government is trying to increase public awareness of the dangers of dengue fever through various campaigns in both the print and electronic media. Another important factor is infection detection. It is expected that the infected individuals can recover from dengue more quickly through the treatment quality in the hospitals.

Based on the description above, we consider a variation of a host-vector model for dengue transmission, including four important factors: media campaign to increase social awareness on dengue transmission, infection detection to hospitalize undetected individuals, limited hospital capacity, and learning it through dengue incidence data from Jakarta. Constructing a mathematical model to describe a disease transmission can be done by several approaches, such as with system of ordinary differential equations [37–40], ordinary differential equations with delay [41], partial differential equation [42], or with fractional order differential equation [43]. Here in this article, we use a eight dimensions system of ordinary differential equations to construct our model. We analyzed our model regarding its equilibrium points and the basic reproduction number. Using the incidence data from Jakarta, we estimate our parameter values and use them to conduct sensitivity analysis.

The presentation of this article is as follows. After we give some literature study and state of the art of our research in this section, the construction of the mathematical model is given in Section 2. The parameter estimation is also conducted in Section 2. Model analysis regarding the dengue-free equilibrium points and the concept of the basic reproduction number is given in Section 3, followed by the analysis of the existence and local stability of the dengue-endemic equilibrium point in Section 4. Local and Global sensitivity analysis on the basic reproduction number and the dynamics of the infected population are given in Section 5. Finally, some conclusions about the important results of our research are given in Section 6.

2. Model description

2.1. Model assumptions, parameters, and variables

Let the human population be divided based on their awareness, health status and treatment that they receive as follows: S denotes susceptible population vulnerable to mosquitoes bites; A denotes susceptible population aware of dengue infection; E denotes the population exposed to dengue; I and H denote the non–hospitalized and hospitalized infected populations, respectively; and R denotes the recovered population that has temporal immunity to dengue infection. On the other hand, the population of mosquitoes is only divided into susceptible and infected mosquitoes, denoted by V and W, respectively. We do not include the recovered stage of mosquitoes owing to its short life-time period, which does not give a chance to mosquitoes to recover from dengue. A transmission diagram to describe all the above interactions between compartments is provided in Fig. 2, and the description of the parameters are given in Table 1.

People entering the human population are assumed to be newborns with a constant rate θ_h and are assumed to be always healthy. Migration is ignored in our model. A susceptible class is a group of people who are vulnerable to dengue and do not have a social awareness. Owing to a media campaign from the government with a constant rate of u_1, there is a transition from susceptible to an awareness compartment. In reality,

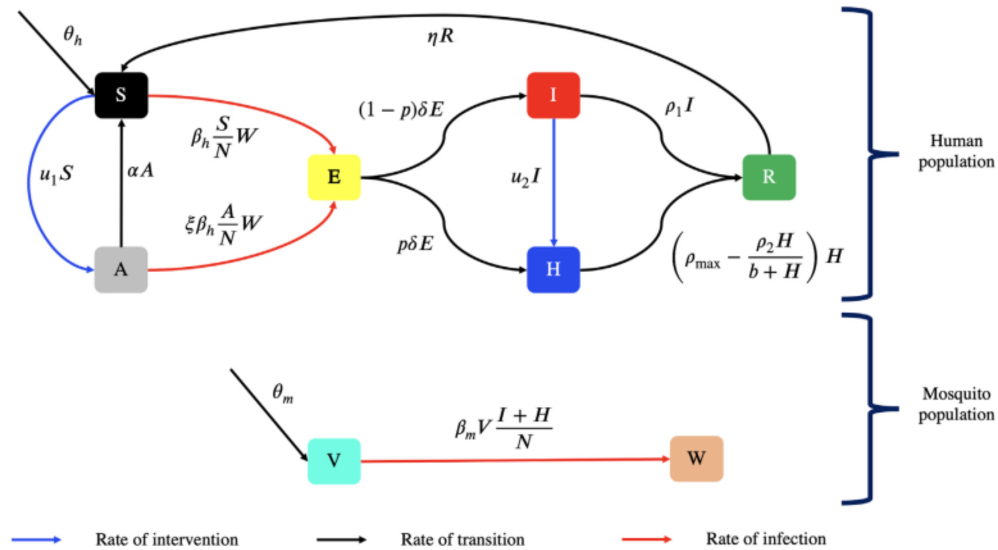


Fig. 2 Transmission diagram of system (1).

Table 1 Description of parameters in system (4).

Par	Description	Units
θ_h	Recruitment rate of human population	$\frac{\text{individual}}{\text{day}}$
θ_m	Recruitment rate of mosquito population	$\frac{\text{mosquitoes}}{\text{day}}$
N	Total of human population	Individual
μ_h	Natural death rate of human population	$\frac{1}{\text{day}}$
μ_m	Natural death rate of mosquitoes' population	$\frac{1}{\text{day}}$
u_1	Rate of media campaign to increase population awareness	$\frac{1}{\text{day}}$
α	Dropout rate owing to loss of awareness	$\frac{1}{\text{day}}$
u_2	Rate of infection detection	$\frac{1}{\text{day}}$
β_h	Infection rate for human population	$\frac{\text{individual}}{\text{day} \times \text{mosquitoes}}$
β_v	Infection rate for mosquitoes' population	$\frac{1}{\text{day}}$
$1-\xi$	Effectiveness of infection reduction due to awareness	-
δ	Transition rate due to virus incubation period	$\frac{1}{\text{day}}$
p	Proportion of new infected individual who get hospitalized	-
ρ_1	Recovery rate	$\frac{1}{\text{day}}$
$\rho_{\max}$	Maximum recovery rate due to hospitalization	$\frac{1}{\text{day}}$
ρ_2	Maximum reduction of $\rho_{\max}$	$\frac{1}{\text{day}}$
η	Waning rate of temporal immunity	$\frac{1}{\text{day}}$

awareness of individuals' awareness of the dangers of dengue is not long-lasting because people will be eventually become careless. Therefore, there is a dropout rate from the awareness to the susceptible compartment, which is denoted by α. The bite of infected mosquitoes can infect both susceptible and aware populations at a constant rate β_h. However, owing of individuals who are aware, the aware individuals have always behaved with caution against dengue by taking many precautions, such as using long arms during outside activities, using anti-mosquito lotion to prevent mosquito bites, etc. Therefore, the infection rate of individuals who are aware can be reduced by a constant parameter, denoted by $\xi \in [0, 1]$. When susceptible and aware individuals get infected, they are categorized as exposed individuals.

After an incubation period of δ^{-1} (approximately eight days), exposed individuals will become infected. However, not all of these newly infected individuals show their symptoms or are detected by the government. Hence, we introduce a probability parameter p, which presents a probability of exposed individuals becoming detected infected individuals and being hospitalized (owing to their symptoms), and $1-p$ being the proportion that they may become undetected infected individuals. The number of hospitalized individuals can increase owing to infection detection u_2. Infected individuals I are assumed to recover at a constant rate ρ_1, whereas the hospitalized individuals recover by $\bar{\rho}$. $\bar{\rho}$ should accommodate the limited hospital capacity, which affects recovery rate of the hospitalized individuals. Hence, $\bar{\rho}$ should fulfill the following assumptions:

1. We assume that the recovery rate of hospitalized individuals should depend on the number of hospitalized individuals. Therefore, $\bar{\rho}$ is a function of the number of hospitalized individuals.
2. Considering a very small number of hospitalized infected individuals, the recovery rate should be at its maximum.
3. Increasing the number of hospitalized individuals will reduce the effectiveness of recovery rate for hospitalized individuals. Hence, we have $\frac{d\bar{\rho}}{dH} < 0$.
4. Regarding an unlimited number of infected individuals sent to the hospital, the recovery rate should be on its minimum value, which is at least the same as the natural recovery rate of non–hospitalized individuals (ρ_1). Therefore, we have $\min(\bar{\rho}) = \lim_{H\to\infty}\bar{\rho} \geqslant \rho_1$.

Based on these assumptions, we choose $\bar{\rho}$ as

$$\left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right),$$

where b measured the availability of treatment supporting instrument, such as bed capacity, number of medical staff, etc. The above function fulfills all the mentioned criteria. Furthermore, we have

$$\lim_{H\to\infty}\left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right) = \rho_{\max} - \rho_2,$$

which is assumed to be approximately equivalent to ρ_1. Finally, the number of recovered individuals increase due to the recovery of infected and hospitalized individuals and decrease because of the loss of temporal immunity at a rate of η. All the human compartments are assumed to decrease due to the natural death rate with a constant rate of μ_h.

As indicated, the total population of female Aedes mosquitoes is only divided into susceptible and infected mosquitoes. Susceptible mosquitoes increase because of newborns with a constant rate of θ_m and decrease owing to dengue infection. Susceptible mosquitoes get infected by dengue after they bite infected individuals in I or H at a constant rate of β_m. Furthermore, the number of susceptible and infected mosquitoes decreases due to the natural death rate μ_m.

2.2. Mathematical model

The mathematical model in this study, which considers media campaigns to increase social awareness, infection detection to hospitalize infected individuals, and limitation of hospital capacity which impacts the recovery rate of infected individuals, is given by the following system of ordinary differential equations:

$$\begin{aligned}
\frac{dS}{dt} &= \theta_h - u_1 S + \alpha A - \beta_h \frac{S}{N} W - \mu_h S + \eta R,\\
\frac{dA}{dt} &= u_1 S - \alpha A - \xi \beta_h \frac{A}{N} W - \mu_h A,\\
\frac{dE}{dt} &= \beta_h W \frac{\xi A + S}{N} - (\delta + \mu_h) E,\\
\frac{dI}{dt} &= (1-p)\delta E - (\rho_1 + \mu_h + u_2) I,\\
\frac{dH}{dt} &= p\delta E + u_2 I - \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right) H - \mu_h H,\\
\frac{dR}{dt} &= \rho_1 I + \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right) H - (\eta + \mu_h) R,\\
\frac{dV}{dt} &= \theta_m - \beta_m V \frac{I+H}{N} - \mu_m V,\\
\frac{dW}{dt} &= \beta_m V \frac{I+H}{N} - \mu_m W,
\end{aligned} \tag{1}$$

where $N = S + A + E + I + H + R$. Before we analyze the model further, it is important to make sure that our model is well-defined and biologically meaningful (The solution should always be non-negative). Hence, we have the following theorem.

Theorem 1. All solutions of the model (1) with a non-negative initial data remain non-negative for all time $t > 0$.

Proof. To proof this theorem, we only need to proof the positiveness of $S(t)$ from the first equation in system (1). The positiveness of $A(t), E(t), E(t), I(t), H(t), R(t), V(t)$, and $W(t)$ can be shown in a similar manner.

Let the initial conditions of $S(t), A(t), E(t), E(t), I(t), H(t), R(t), V(t)$, and $W(t)$, i.e.

$$S(0), A(0), E(0), E(0), I(0), H(0), R(0), V(0), W(0),$$

be non-negative. The following differential inequality holds from $\frac{dS}{dt}$:

$$\frac{dS}{dt} > -\left(u_1 + \beta_h \frac{W(s)}{N(s)} + \mu_h\right) S. \tag{2}$$

Using the integrating factor

$$\exp\left(\int_0^t u_1 + \beta_h \frac{W(s)}{N(s)} + \mu_h\right) ds,$$

to (2), and solve it respect to $S(t)$ gives:

$$\begin{aligned}
S(t) &> S(0)\exp\left[-\left(\int_0^t \beta_h \frac{W(s)}{N(s)} ds + u_1 t + \mu_h t\right)\right]\\
&> 0, \quad \forall\ t > 0.
\end{aligned} \tag{3}$$

Hence, the solution $S(t)$ is non-negative for all time $t > 0$. Similarly, we also can show that $A(t), E(t), E(t), I(t), H(t), R(t), V(t)$, and $W(t)$ are also non-negative for all time $t > 0$. Here the proof is complete. □

Because the life expectancy of mosquitoes is shorter than that of humans ($\mu_m^{-1} \ll \mu_h^{-1}$), we understand that the mosquito population has a faster dynamic, compared to the human population, to reach its equilibrium point. Hence, we use the Quasi Steady-State Approximation (QSSA) method to approach system (1) when the mosquito population has already reached its equilibrium. Therefore, solving $\frac{dV}{dt} = 0$ and $\frac{dW}{dt} = 0$ considering V and W, we obtain

$$V^* = \frac{\theta_m N}{\beta_m (H+I) + \mu_m N},$$
$$W^* = \frac{\theta_m \beta_m (H+I)}{(\beta_m (H+I) + \mu_m N)\mu_m}.$$

Furthermore, we use the same assumption as in [33,44], where $\beta_m \mu_m = \frac{1}{2}$. Since we assume that N is constant, let $\beta_h \frac{\theta_m}{\mu_m N} = \beta$ and $2\mu_m^2 = \mu_v$. Substituting V^* and W^* into system (1), we simplify system (1) as follows:

$$\begin{aligned}
\frac{dS}{dt} &= \theta_h - u_1 S + \alpha A - \frac{\beta S (H+I)}{H+I+\mu_v N} - \mu_h S + \eta R,\\
\frac{dA}{dt} &= u_1 S - \xi \frac{\beta A (H+I)}{H+I+\mu_v N} - (\mu_h + \alpha) A,\\
\frac{dE}{dt} &= \frac{\beta (S + \xi A)(H+I)}{H+I+\mu_v N} - (\delta + \mu_h) E,\\
\frac{dI}{dt} &= (1-p)\delta E - (\rho_1 + \mu_h + u_2) I,\\
\frac{dH}{dt} &= p\delta E + u_2 I - \mu_h H - \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right) H,\\
\frac{dR}{dt} &= \rho_1 I + \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right) H - (\eta + \mu_h) R.
\end{aligned} \tag{4}$$

Based on the QSSA approach using the fast dynamics of mosquitoes, the model in system (4) is simpler to analyze, both for dynamical analysis and parameter estimation. We observe that only μ_v, parameters from the mosquito population, appear in our model (which is known from several studies), whereas θ_m merges with β_h and N in β.

2.3. Parameter estimation

To justify the parameters on our model in system (4), we need a time series of dengue incidence data. Model fitting involves parameter estimation, which indicates an identification of the parameter values that can fit our model to the existing data. To perform our parameter estimation, we minimize the Euclidian distance between the incidence data H^{data} and the solution of H^{model} in our model (4) using the best-fit parameter: $\rho_{\max}, u_1, u_2, \alpha, \beta, \xi, p$, and b. Hence, we define our objective function as:

$$\mathcal{J} = \int_0^T \left(H^{\text{data}} - H^{\text{model}}\right)^2 dt, \tag{5}$$

where T is the final time of existence of the incidence data. Hence, we aim to seek the optimal parameters $\rho^*_{\max}, u^*_1, u^*_2, \alpha^*, \beta^*, \xi^*, p^*$, and b^* such that

$$\begin{aligned}&\mathcal{J}(\rho^*_{\max}, u^*_1, u^*_2, \alpha^*, \beta^*, \xi^*, p^*, b^*)\\ &= \min_{\Theta} \mathcal{J}(\rho_{\max}, u_1, u_2, \alpha, \beta, \xi, p, b),\end{aligned} \tag{6}$$

where Θ is the admissible value of the estimated parameter.

To estimate our parameter values, we use dengue incidence data from 154 hospitals in Jakarta by the Epidemiology Department, Jakarta Health Office, Indonesia from 1st January 2020 to 31st December 2020. The data describes all the recorded data from the hospital, which are relevant to variable H on system (4). We use the "fmincon" toolbox, a nonlinear programming solver available in Matlab. The result is shown in Fig. 3, and the parameters values are demonstrated in Table 2.

Considering the results of the calculations, it was found that the basic reproduction number of dengue in Jakarta in 2019 was 0.491. This confirms the dynamic behavior of the data on the number of people in the hospital, which continued to decrease toward zero after reaching its outbreak in mid-March 2020. Many studies have linked the close relationship between high rainfall and the increasing numbers of dengue cases shortly after the rainfall peak [31,33,34]. In Indonesia, the rainfall season occurs in October/November to March/April, where the peak occurs during approximately January/February. The increasing amount of rainfall in that period increases the number of dengue cases in Jakarta. We observe that dengue cases in 2020 reach their peak in March, or one month after the peak of rainfall. The occurrence of this time lag can be because of the delaying period for mosquito growth from the larval stage to adult mosquitoes that are ready to infect humans, which takes approximately one month.

3. Model analysis

3.1. Disease-free equilibrium and the basic reproduction number

System (4) has a disease-free equilibrium which is expressed as follows:

$$\begin{aligned}\mathcal{E}_1 &= (S, A, E, I, H, R)\\ &= \left(\frac{\theta_h(\alpha+\mu_h)}{\mu_h(\alpha+u_1+\mu_h)}, \frac{\theta u_1}{\mu_h(\alpha+u_1+\mu_h)}, 0, 0, 0, 0\right)\end{aligned} \tag{7}$$

Subsequently, we calculate the basic reproduction number of our proposed model in system (4). Basic reproduction number, denoted by $\mathcal{R}_0$, presents the expected number of secondary cases caused by one primary case during its infection period. Considering several epidemiological models [45–50], the related basic reproduction number explains the qualitative behavior of their models, such as the existence and disappearance of the disease. Regarding several cases, it was found that the disease always persisted if the basic reproduction number was larger than one and possibly died out if it was smaller than one. In this study, we use the next-generation matrix approach [51] to calculate our related basic reproduction number.

The infected compartments of system (4) consists of E, I, H and R. Let $x = (E, I, H, R)$ and rewrite system (4) as follows:

$$\frac{dx}{dt} = \mathcal{F}(x) - \mathcal{V}(x), \tag{8}$$

where $\mathcal{F} = [\mathcal{F}_i]$ and $\mathcal{V} = [\mathcal{V}^-_i - \mathcal{V}^+_i]$ for $i = 1, 2, 3, 4$ is expressed as:

$$\mathcal{F} = \begin{bmatrix}\frac{\beta(S+\xi A)(D+I)}{D+I+\mu_v N}\\ 0\\ 0\\ 0\end{bmatrix},$$

$$\mathcal{V} = \begin{bmatrix}(\delta+\mu_h)E\\ (1-p)\delta E(\rho_1+\mu_h+u_2)I\\ p\delta E + u_2 I - \mu_h H - \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right)H\\ \rho_1 I + \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right)H - (\eta+\mu_h)R\end{bmatrix}. \tag{9}$$

Thereafter, the corresponding Jacobian matrix of $\mathcal{F}$ evaluated at the dengue-free equilibrium $\mathcal{E}_1$ is given by:

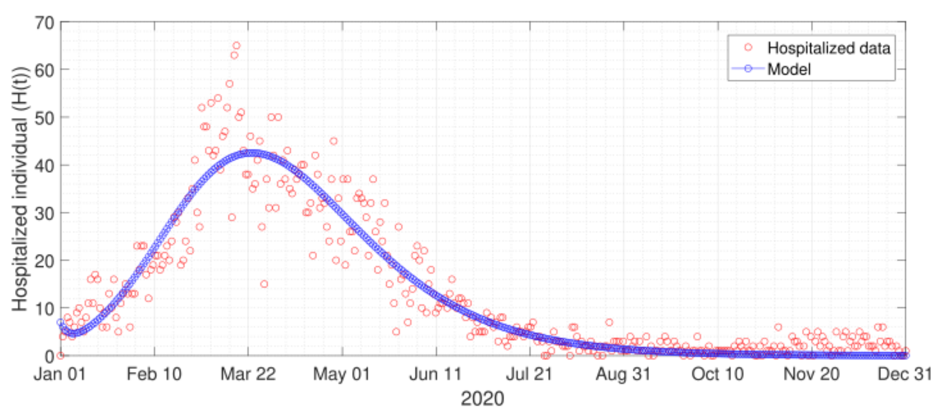


Fig. 3 Parameter estimation results of the hospitalized daily date in Jakarta during 2020.

Table 2 Baseline parameter values for the model in system (4)

Par	Estimated values	Sources	Par	Estimated values	Sources
θ_h	$\frac{10\,560\,000}{71.35\times 365}$	Estimated	μ_h	$\frac{1}{71.35\times 365}$	Estimated
μ_v	$\frac{2}{21^2}$	Estimated	η	$\frac{1}{36}$	Estimated
δ	$\frac{1}{8}$	Estimated	ρ_1	$\frac{1}{14}$	Estimated
$\rho_{\max}$	0.234	Fitted	N	10 560 000	Estimated
u_1	0.028	Fitted	u_2	0.055	Fitted
α	0.004	Fitted	β	0.002	Fitted
ξ	1.17×10^{-6}	Fitted	p	0.169	Fitted
b	9382	Fitted			

$$F=\begin{bmatrix}0 & \frac{\beta\theta_h(\xi u_1+\alpha+\mu_h)}{\mu_h(\alpha+\mu_h+u_1)\mu_v N} & \frac{\beta\theta_h(\xi u_1+\alpha+\mu_h)}{\mu_h(\alpha+\mu_h+u_1)\mu_v N} & 0\\ 0&0&0&0\\ 0&0&0&0\\ 0&0&0&0\end{bmatrix},$$

and the corresponding Jacobian matrix of $\mathcal{V}$ evaluated at the dengue-free equilibrium $\mathcal{E}_1$ is given by:

$$V=\begin{bmatrix}-\delta-\mu_h & 0 & 0 & 0\\ -(-1+p)\delta & -\rho_1-u_2-\mu_h & 0 & 0\\ p\delta & u_2 & -\mu_h-\rho_{\max} & 0\\ 0 & \rho_1 & \rho_{\max} & -\eta-\mu_h\end{bmatrix}.$$

Because we have two zero rows in F, the next-generation matrix of system (4) is given by:

$$\begin{aligned}K&=-E\prime FV^{-1}E\\ &=\left[\frac{\beta(\xi u_1+\alpha+\mu_h)\delta(p\rho_1+\mu_h+\rho_{\max}(1-p)+u_2)}{(\alpha+\mu_h+u_1)\mu_v(\delta+\mu_h)(\rho_1+u_2+\mu_h)(\mu_h+\rho_{\max})}\right],\end{aligned}\quad(10)$$

where $E=\begin{bmatrix}1\\0\\0\\0\end{bmatrix}$, and $E\prime$ is the transpose of E. Therefore, the basic reproduction number of model (4) is given by:

$$\mathcal{R}_0=\frac{\beta(\xi u_1+\alpha+\mu_h)\delta(p\rho_1+\mu_h+\rho_{\max}(1-p)+u_2)}{(\alpha+\mu_h+u_1)\mu_v(\delta+\mu_h)(\rho_1+u_2+\mu_h)(\mu_h+\rho_{\max})}.\quad(11)$$

Based on the above expression on $\mathcal{R}_0$, we obtain the following theorem.

Theorem 2. The disease-free equilibrium $\mathcal{E}_1$ of system (4) is locally asymptotically stable if $\mathcal{R}_0<1$, and it is unstable if $\mathcal{R}_0>1$.

Proof. The proof is based on Theorem 2 in [52]. This can also be proven by the linearization of system (4) at $\mathcal{E}_1$ and by verifying that all the real parts of the eigenvalues are negative. If there exists at least one positive eigenvalue, then $\mathcal{E}_1$ is unstable.

To use Theorem 2 in [52], let us simplify the notation of variables in system (4) as follows: $x_i\in(E,I,H,R,S,A)$ for $i=1,2,\ldots,6$. Hence, the non-susceptible variables are $x_{id}\in(E,I,H,R)$ for $i=1,2,3,4$, and $x_{is}\in(S,A)$ for $i=5,6$ is for the susceptible variables. To use the result from [52], our system should fulfill five conditions in [52]. Let us rewrite system (4) as

$$\dot{x}_i=\mathcal{F}_i-\mathcal{V}_i,$$

where

$$\mathcal{F}=\begin{bmatrix}\frac{\beta(S+\xi A)(D+I)}{D+I+\mu_v N}\\0\\0\\0\\0\\0\end{bmatrix},$$

$$\mathcal{V}=\begin{bmatrix}(\delta+\mu_h)E\\ (1-p)\delta E(\rho_1+\mu_h+u_2)I\\ p\delta E+u_2 I-\mu_h H-\left(\rho_{\max}-\frac{\rho_2 H}{b+H}\right)H\\ \rho_1 I+\left(\rho_{\max}-\frac{\rho_2 H}{b+H}\right)H-(\eta+\mu_h)R\\ \theta_h-u_1 S+\alpha A-\frac{\beta S(D+I)}{D+I+\mu_v N}-\mu_h S+\eta R\\ u_1 S-\xi\frac{\beta A(D+I)}{D+I+\mu_v N}-(\mu_h+\alpha)A\end{bmatrix},$$

where $\mathcal{V}=\mathcal{V}^{-}-\mathcal{V}^{+}$. Note that $\mathcal{V}^{-}-\mathcal{V}^{+}$ are given by

$$\mathcal{V}^{-}=\begin{bmatrix}(\delta+\mu_h)E\\ (\rho_1+\mu_h+u_2)I\\ \mu_h H+\left(\rho_{\max}+\frac{\rho_2 H}{b+H}\right)H\\ (\eta+\mu_h)R\\ u_1 S+\frac{\beta S(D+I)}{D+I+\mu_v N}+\mu_h S\\ \xi\frac{\beta A(D+I)}{D+I+\mu_v N}+(\mu_h+\alpha)A\end{bmatrix},$$

$$\mathcal{V}^{+}=\begin{bmatrix}0\\ (1-p)\delta E\\ p\delta E+u_2 I\\ \rho_1 I+\left(\rho_{\max}-\frac{\rho_2 H}{b+H}\right)H\\ \theta_h+\alpha A+\eta R\\ u_1 S\end{bmatrix}.$$

Subsequently, we provide proofs for the five axioms in [52] to show that $\mathcal{E}_1$ is locally asymptotically stable when $\mathcal{R}_0<1$.

1. *If* $x_i \geqslant 0$, *then* $\mathcal{F}_i, \mathcal{V}_i^-$, *and* $\mathcal{V}_i^+$ *is non-negative for* $i = 1,2,\ldots 6$. By substituting $x_i \geqslant 0$ for $i = 1,2,\ldots 6$ into $\mathcal{F}_i, \mathcal{V}_i^-$ and $\mathcal{V}_i^+$, it can be observed that $\mathcal{F}_i, \mathcal{V}_i^-$, and $\mathcal{V}_i^+$ are always non-negative.
2. *If a compartment is empty, then there is no out-flow transfer from each compartment.* It can also be observed that when $x_i = 0$ for $i = 1,2,\ldots 6$, then $\mathcal{V}_i^- = 0$. Furthermore, if $x_i \in \mathcal{E}_1$, then we can obtain $\mathcal{V}_i^- = 0$ for $i = 1,2,3,4$.
3. *Considering* $i > 4$, *then* $\mathcal{F}_i = 0$. regarding the expression of $\mathcal{F}$ above, it can be observed that $\mathcal{F}_5 = \mathcal{F}_6 = 0$. Hence, the infection incidence in the non-infected compartment (S, A) is zero.
4. *If* $x_i \in \mathcal{E}_1$, *then* $\mathcal{F}_i = 0$ *and* $\mathcal{V}_i^+ = 0$ *for* $i = 1,2,3,4$. We realize that $\mathcal{F}_i$ is always zero for $i = 2,3,4$. On the contrary, $\mathcal{F}_1(\mathcal{E}_1) = 0$. Furthermore, $\mathcal{V}_i^+$ is also always zero when $x_i \in \mathcal{E}_1$.
5. *If* $\mathcal{F}(x) = 0$, *then all the eigenvalues of the Jacobian matrix evaluated at* $\mathcal{E}_1$ *(denoted by* $Df(\mathcal{E}_1)$*) have a negative real part*. We have $f_i(x)$ for $i = 1,2,\ldots 6$, which denotes $dE/dt, dI/dt, dH/dt, dR/dt, dS/dt$, and dA/dt, respectively. Hence, when $\mathcal{F}(x) = 0$, we obtain no new incidence in the model, indicating that we obtain system (4) as follows:

$$
\begin{aligned}
\frac{dE}{dt} &= -(\delta + \mu_h)E,\\
\frac{dI}{dt} &= (1-p)\delta E - (\rho_1 + \mu_h + u_2)I,\\
\frac{dH}{dt} &= p\delta E + u_2 I - \mu_h H - \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right)H,\\
\frac{dR}{dt} &= \rho_1 I + \left(\rho_{\max} - \frac{\rho_2 H}{b+H}\right)H - (\eta + \mu_h)R,\\
\frac{dS}{dt} &= \theta_h - u_1 S + \alpha A - \mu_h S + \eta R,\\
\frac{dA}{dt} &= u_1 S - \xi\frac{\beta A(D+I)}{D+I+\mu_v N} - (\mu_h + \alpha)A.
\end{aligned}
$$

Therefore, the Jacobian matrix of the above system evaluated at $\mathcal{E}_1$ ($Df(\mathcal{E}_1)$) is expressed as:

$$
\begin{bmatrix}
-u_1-\mu_h & \alpha & 0 & 0 & 0 & \eta\\
u_1 & -\alpha-\mu_h & 0 & 0 & 0 & 0\\
0 & 0 & -\delta-\mu_h & 0 & 0 & 0\\
0 & 0 & -(-1+p)\delta & -\rho_1-u_2-\mu_h & 0 & 0\\
0 & 0 & p\delta & u_2 & -\mu_h-\rho_{\max} & 0\\
0 & 0 & 0 & \rho_1 & \rho_{\max} & -\eta-\mu_h
\end{bmatrix}.
$$

Hence, the eigenvalues of $Df(\mathcal{E}_1)$ are $-(\delta+\mu_h), -\mu_h, -(\alpha+\mu_h+u_1), -(\rho_1+u_2+\mu_h), -(\mu_h+\rho_{\max})$, and $-(\eta+\mu_h)$. Because all the parameters are positive, we assume that all eigenvalues of $Df(\mathcal{E}_1)$ have a negative real part.

Because all the axioms are fulfilled, we can conclude that $\mathcal{E}_1$ is locally asymptotically stable when $\mathcal{R}_0 < 1$, and it is unstable when $\mathcal{R}_0 > 1$. □

The existence of this theorem guarantees a condition such that the probability of the disappearance of dengue from the population can be achieved. In this case, the condition is $\mathcal{R}_0 < 1$. If we observe closely, the number $\mathcal{R}_0$ is composed of the parameters involved in the proposed dengue model. One of them is the infection rate parameter β, which is directly proportional to $\mathcal{R}_0$. That is, the greater the rate of dengue infection, the greater the value of $\mathcal{R}_0$, and the more difficult it is to eliminate dengue disease from the community. Further discussion regarding the effect of model parameters on basic reproduction numbers, dynamics of dengue disease, and its global sensitivity will be discussed in the following chapter.

4. Existence of the non-trivial equilibrium

4.1. No saturation on the hospitalized individual recovery rate

Considering a simple case in which there is no saturation on the hospitalized individual recovery rate ($\rho_2 = 0, b = 0$), we assume that $\bar{\rho} = \rho_{\max}$. Hence, system (4) can be simplified as:

$$
\begin{aligned}
\frac{dS}{dt} &= \theta_h - u_1 S + \alpha A - \frac{\beta S(D+I)}{D+I+\mu_v N} - \mu_h S + \eta R,\\
\frac{dA}{dt} &= u_1 S - \xi\frac{\beta A(D+I)}{D+I+\mu_v N} - (\mu_h + \alpha)A,\\
\frac{dE}{dt} &= \frac{\beta(S+\xi A)(D+I)}{D+I+\mu_v N} - (\delta + \mu_h)E,\\
\frac{dI}{dt} &= (1-p)\delta E - (\rho_1 + \mu_h + u_2)I,\\
\frac{dH}{dt} &= p\delta E + u_2 I - \mu_h H - \rho_{\max} H,\\
\frac{dR}{dt} &= \rho_1 I + \rho_{\max} H - (\eta + \mu_h)R.
\end{aligned}
\tag{12}
$$

Regarding this assumption, the form of the disease-free equilibrium and the basic reproduction number are the same as for the complete model. Considering the non-trivial equilibrium, it is difficult to demonstrate it explicitly as a function for all the parameters in system (12). Hence, we calculate the form of the non-trivial equilibrium (later known as the endemic equilibrium) and yield:

$$\mathcal{E}_2^* = (S, A, E, I, H, R) = (S^*, A^*, E^*, I^*, H^*, R^*), \tag{13}$$

where

$$
\begin{aligned}
S^* &= \frac{(\alpha A^* + \eta R^* + \theta_h)(N\mu_v + H^* + I^*)}{N\mu_h\mu_v + N\mu_v u_1 + \beta H^* + \mu_h H^* + H^* u_1 + i\beta + i\mu_h + I^* u_1},\\
A^* &= \frac{S^* u_1 (N\mu_v + H^* + I^*)}{H^*\beta\xi + I^*\beta\xi + N\alpha\mu_v + N\mu_h\mu_v + H^*\alpha + \mu_h H^* + I^*\alpha + \mu_h I^*},\\
E^* &= \frac{\left(\mu_h^2 + \mu_h\rho_1 + \mu_h\rho_{\max} + \mu_h u_2 + \rho_1\rho_{\max} + \rho_{\max} u_2\right)H}{\delta(p\mu_h + p\rho_1 + u_2)},\\
I^* &= \frac{(\mu_h + \rho_{\max})(1-p)H}{p\mu_h + p\rho_1 + u_2},\\
R^* &= \left(\frac{H(p\mu_h\rho_{\max} + \mu_h\rho_1 + \rho_1\rho_{\max}(1-p) + \rho_{\max} u_2)}{\eta p\mu_h + \eta p\rho_1 + p\mu_h^2 + p\mu_h\rho_1 + \eta u_2 + \mu_h u_2}\right).
\end{aligned}
$$

On the contrary, H^* is considered from the positive root of the following second-degree polynomial

$$g(H) = a_2 H^2 + a_1 H + a_0, \tag{14}$$

where $a_2 > 0, a_1$ has a long expression that can be positive or negative, and

$$a_0 = (\alpha + \mu_h + u_1)\mu_v(\delta + \mu_h)(\rho_1 + u_2 + \mu_h)(\mu_h + \rho_{\max})(1 - \mathcal{R}_0).$$

Because $a_0 < 0 \Longleftrightarrow \mathcal{R}_0 > 1$ and a_2 is always positive, we obtain the following theorem.

Theorem 3. The simple case model in system (12) always has a unique endemic equilibrium when $\mathcal{R}_0 > 1$.

Furthermore, because the polynomial $g(H)$ is a second-degree polynomial and a_1 can be positive or negative, it is possible to achieve another endemic equilibrium when $\mathcal{R}_0 < 1$. The condition for the existence/disappearance of the endemic equilibrium is as follows:

1. There can be one endemic equilibrium if $\mathcal{R}_0 > 1$.

2. There can be two distinct endemic equilibriums when $\mathcal{R}_0 < 1, a_1 < 0$, and $a_1^2 - 4a_2a_0 > 0$.
3. There can be two identical endemic equilibriums when $\mathcal{R}_0 < 1, a_1 < 0$, and $a_1^2 - 4a_2a_0 = 0$.
4. There may be no endemic equilibrium when $\mathcal{R}_0 < 1$ and $a_1 > 0$.

The results above show the possibility of having multiple endemic equilibrium points when $\mathcal{R}_0 < 1$. This phenomenon is highly related to the existence of backward bifurcation phenomena. However, we focus on interpreting our model on the media campaign's impact to raise population awareness and case detection in the dengue control program. Therefore, we leave the existence and bifurcation analysis on the endemic equilibrium point as an open problem in this study. Our previous study contains details of the existence of endemic equilibrium analysis and the use of Castillo-Song bifurcation theorem [53] for the bifurcation analysis in several epidemiological models [45,46,54–56].

4.2. Numerical experiment on a complete model

To perform a numerical experiment on the existence and stability of the endemic equilibrium of the complete model in system (4), we use the same parameter values as in Table 2, excluding $\beta = 0.006$. Considering this set of parameters, we use $\mathcal{R}_0 = 1.47$, which is larger than one. Hence, considering Theorem 2, the disease-free equilibrium $\mathcal{E}_1$ is unstable. Substituting all the parameters on system (4), we obtain:

$$\begin{aligned}
\frac{dS}{dt} &= 405.4 - 0.028S + 0.004A - \frac{0.006S(H+I)}{H+I+47891.1} + 0.027R,\\
\frac{dA}{dt} &= 0.028S - \frac{7.2\times10^{-9}S(H+I)}{H+I+47891.1} - 0.004A,\\
\frac{dE}{dt} &= \frac{0.006(1.17\times10^{-6}A+S)(H+I)}{H+I+47891.1} - 0.125E,\\
\frac{dI}{dt} &= 0.104E - 0.126I,\\
\frac{dH}{dt} &= 0.021E - 0.000038H - \left(0.234 - \frac{0.162H}{9382+H}\right)H + 0.055I,\\
\frac{dR}{dt} &= \left(0.234 - \frac{0.162H}{9382+H}\right)H + 0.071I - 0.027R.
\end{aligned} \tag{15}$$

We assume that the right-hand side of system (15) equals zero and solve it considering all the variables. This achieves a disease-free equilibrium as follows:

$$\mathcal{E}_1^{\dagger} = (S, A, E, I, H, R) = (1.33 \times 10^6, 9.22 \times 10^6, 0, 0, 0, 0),$$

and the endemic equilibrium is expressed as follows:

$$\begin{aligned}
\mathcal{E}_2^{\dagger} &= (S, A, E, I, H, R)\\
&= (1.3 \times 10^6, 9.07 \times 10^6, 25458, 20910, 11715, 114361).
\end{aligned}$$

To analyze the local stability of each equilibrium, we linearize system (15) on the respected equilibrium point. The linearized system (15) at $\mathcal{E}_1^{\dagger}$ obtains

$$J_{\mathcal{E}_1^{\dagger}} = \begin{bmatrix}
-0.028 & 0.004 & 0 & -0.166 & -0.166 & 0.027\\
0.028 & -0.004 & 0 & -0.00000135 & -0.00000135 & 0\\
0 & 0 & -0.125 & 0.166 & 0.166 & 0\\
0 & 0 & 0.103 & -0.126 & 0 & 0\\
0 & 0 & 0.021 & 0.055 & -0.23 & 0\\
0 & 0 & 0 & 0.07 & 0.234 & -0.027
\end{bmatrix}.$$

The eigenvalues of $J_{\mathcal{E}_1^{\dagger}}$ are

$$\lambda_1 = -0.03, \quad \lambda_2 = -3.8 \times 10^{-6}, \quad \lambda_3 = 0.026,$$
$$\lambda_4 = -0.027, \quad \lambda_5 = -0.255 + 0.04i, \quad \lambda_6 = -0.255 - 0.04i.$$

Since $\lambda_3 > 0$, we conclude that $\mathcal{E}_1^{\dagger}$ is unstable.

Considering the same approach, the linearized matrix of system (15) on $\mathcal{E}_2^{\dagger}$ is given by

$$J_{\mathcal{E}_2^{\dagger}} = \begin{bmatrix}
-0.03 & 0.004 & 0 & -0.05 & -0.05 & 0.027\\
0.028 & -0.004 & 0 & -4.7\times10^{-7} & -4.7\times10^{-7} & 0\\
0.002 & 2.84\times10^{-9} & -0.125 & 0.05 & 0.05 & 0\\
0 & 0 & 0.103 & -0.126 & 0 & 0\\
0 & 0 & 0.021 & 0.055 & -0.104 & 0\\
0 & 0 & 0 & 0.071 & 0.104 & -0.02
\end{bmatrix},$$

with eigenvalues

$$\lambda_1 = -0.03 + 0.015i, \; \lambda_2 = -0.03 - 0.015i, \; \lambda_3 = -0.000038,$$
$$\lambda_4 = -0.168 + 0.007i, \; \lambda_5 = -0.168 - 0.007i, \; \lambda_6 = -0.01.$$

Because all the real parts of the eigenvalues are negative, we can conclude that $\mathcal{E}_2^{\dagger}$ is locally asymptotically stable for a set of parameters such that $\mathcal{R}_0 > 1$.

5. Sensitivity analysis

5.1. Sensitivity analysis on $\mathcal{R}_0$

To investigate graphically how $\mathcal{R}_0$ varies considering media campaigns and infection detection, we use parameters as shown in Table 2 except $\beta = 0.006$, and let u_1 and u_2 be free parameters. Substituting the mentioned parameter values with $\mathcal{R}_0$ provides

$$\mathcal{R}_0(u_1, u_2) = \frac{5.65(.004 + 1.17 \times 10^{-6}u_1)(0.206 + u_2)}{(0.004 + u_1)(0.071 + u_2)}.$$

The level set of $\mathcal{R}_0$ considering u_1 and u_2 is provided in Fig. 4. We observe that increasing the value of media campaign and infection detection can reduce the basic reproduction significantly. The critical values of media campaign to reach a condition $\mathcal{R}_0 < 1$ when no infection detection is involved in the model is 0.062. On the contrary, it is not probable that the infection detection can reach a condition $\mathcal{R}_0 < 1$ when no media campaign is implemented in the field. Hence, the critical value of infection detection such that $\mathcal{R}_0 < 1$ depends on the intensity of media campaign. Precisely, the condition of u_2 is such that $\mathcal{R}_0 < 1$ is given by

$$u_2 > \frac{10^{-3}(71.56u_1 - 4.42)}{1.87 - 99u_1}.$$

Hence, we observe that a higher intensity of media campaign will reduce the minimum infection detection rate to eradicate dengue from the population. This is shown in Fig. 5.

Subsequently, we will determine the most elastic parameter on $\mathcal{R}_0$ using the best-fit parameters in Table 2. To conduct this elasticity analysis, we use the following formula:

$$\Gamma_{\mathcal{R}_0}^{s} = \frac{\partial \mathcal{R}_0}{\partial s} \times \frac{s}{\mathcal{R}_0}, \tag{16}$$

where s is the set of parameters in $\mathcal{R}_0$ [57]. For example, we have the elasticity of $\mathcal{R}_0$ considering u_1 as:

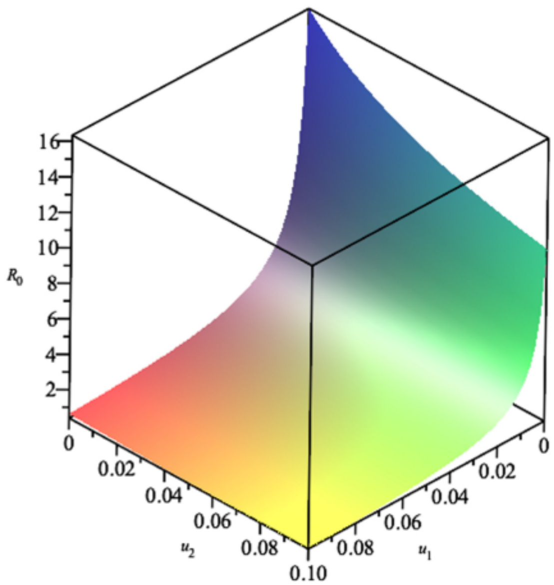


Fig. 4 Level set of $\mathcal{R}_0$ respect to u_1 and u_2.

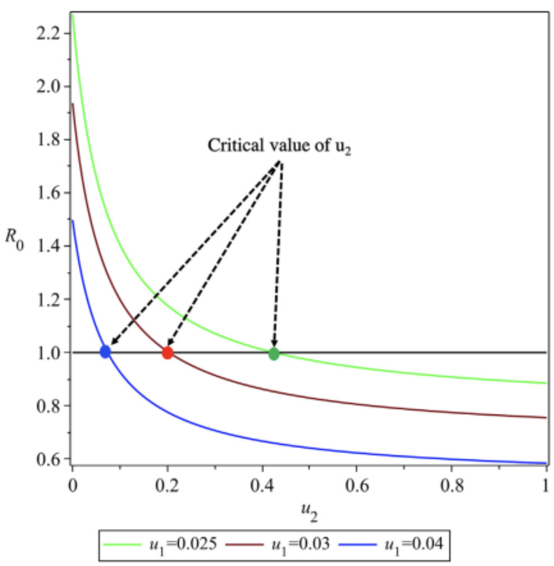


Fig. 5 Dependency of critical values of infection detection rate considering various values of media campaign.

$$\Gamma^{u_1}_{\mathcal{R}_0} = \frac{\partial \mathcal{R}_0}{\partial u_1} \times \frac{u_1}{\mathcal{R}_0} = -\frac{(\alpha + \mu_h)(1 - \xi)u_1}{(\xi u_1 + \alpha + \mu_h)(\alpha + \mu_h + u_1)}. \quad (17)$$

We observe that $\Gamma^{u_1}_{\mathcal{R}_0} < 0$ for all parameter values. Therefore, we also assume that increasing u_1 will reduce $\mathcal{R}_0$. Furthermore, substituting the parameter value in Table 2, we observe that $\Gamma^{u_1}_{\mathcal{R}_0} = -0.87$. Therefore, we can conclude that increasing media campaign intensity for 10% will **reduce** $\mathcal{R}_0$ for 8.7%. Similarly, we obtain the elasticity of $\mathcal{R}_0$ considering that the infection detection rate u_2 is expressed as:

$$\begin{aligned} \Gamma^{u_2}_{\mathcal{R}_0} &= \frac{\partial \mathcal{R}_0}{\partial u_2} \times \frac{u_2}{\mathcal{R}_0} \\ &= -\frac{(\rho_{max} - \rho_1)(1-p)u_2}{(p\rho_1 - p\rho_{max} + \mu_h + \rho_{max} + u_2)(\rho_1 + u_2 + \mu_h)} \end{aligned} \quad (18)$$

Evaluating $\Gamma^{u_2}_{\mathcal{R}_0}$ with parameter values in Table 2 achieves -0.22. Hence, we assume that increasing the infection detection rate for 10% will reduce $\mathcal{R}_0$ for 2.2%. Furthermore, we observe that using the best-fit parameter for incidence data in Jakarta, the media campaign is a more promising effort to control the spread of dengue in Jakarta because $\Gamma^{u_1}_{\mathcal{R}_0} > \Gamma^{u_2}_{\mathcal{R}_0}$. The complete results for the elasticity of $\mathcal{R}_0$ considering all the parameters in $\mathcal{R}_0$ is presented in Table 3.

Considering the elasticity analysis in Table 3, we observe that the most influential parameters to $\mathcal{R}_0$ controllable in the field are μ_v and β, which represent the death rate of mosquitoes and the infection rate, respectively. Hence, increasing μ_v or reducing β is very common in the field. This includes the use of fumigation or larvicide to control the mosquito population or the use of mosquito repellent or long-sleeved clothes to reduce the infection rate.

The elasticity value in Table 3 depends on the value of the parameter that is being used. Our aim is to understand the impact of media awareness and case detection rate on how these two interventions impact the size of $\mathcal{R}_0$. Hence, it is crucial to verify the dynamic of the elasticity of $\mathcal{R}_0$ considering these two interventions. Substituting the parameter values in Table 2, excluding u_1 and u_2 to formula in (17) and (18), we obtain the dynamic of $\Gamma^{u_1}_{\mathcal{R}_0}$ and $\Gamma^{u_2}_{\mathcal{R}_0}$ considering u_1 and u_2 in Fig. 6.

Considering Fig. 6a and b, when both form of intervention are implemented together, then $\Gamma^{u_1}_{\mathcal{R}_0}$ and $\Gamma^{u_2}_{\mathcal{R}_0}$ are always negative. We observe that $\Gamma^{u_1}_{\mathcal{R}_0}$ is monotonically decreasing, indicating that if a more intense media campaign is implemented, the reduction of $\mathcal{R}_0$ will be more significant. However, when $u_1 > 0.2$, the changes in $\Gamma^{u_1}_{\mathcal{R}_0}$ is no longer significant (indicated by a small slope). Hence, increasing the media campaign for $u_1 > 0.2$ will not achieve significant changes. Contrary to $\Gamma^{u_1}_{\mathcal{R}_0}$, the value of $\Gamma^{u_2}_{\mathcal{R}_0}$ does not always decrease monotonically. We observe that the maximum value of $|\Gamma^{u_2}_{\mathcal{R}_0}|$ is obtained when $u_2 = 0.125$. Hence, increasing the intensity of case detection for more than 0.125 will not continuously achieve a better result. This phenomenon is closely related to the difference between the natural healing rate (ρ_1) and the maximum recovery rate obtained by hospitalized individuals ($\rho_{\max}$). The greater the difference between $\rho_{\max}$ and ρ_1, the greater the value of $\Gamma^{u_2}_{\mathcal{R}_0}$ is, and the value of u_2 is such that $\Gamma^{u_2}_{\mathcal{R}_0}$ becomes increases monotonically considering u_2. For example, when we increase $\rho_{\max}$ to 0.234, $\Gamma^{u_2}_{\mathcal{R}_0}$ obtains its maximum elasticity at $u_2 = 0.144$.

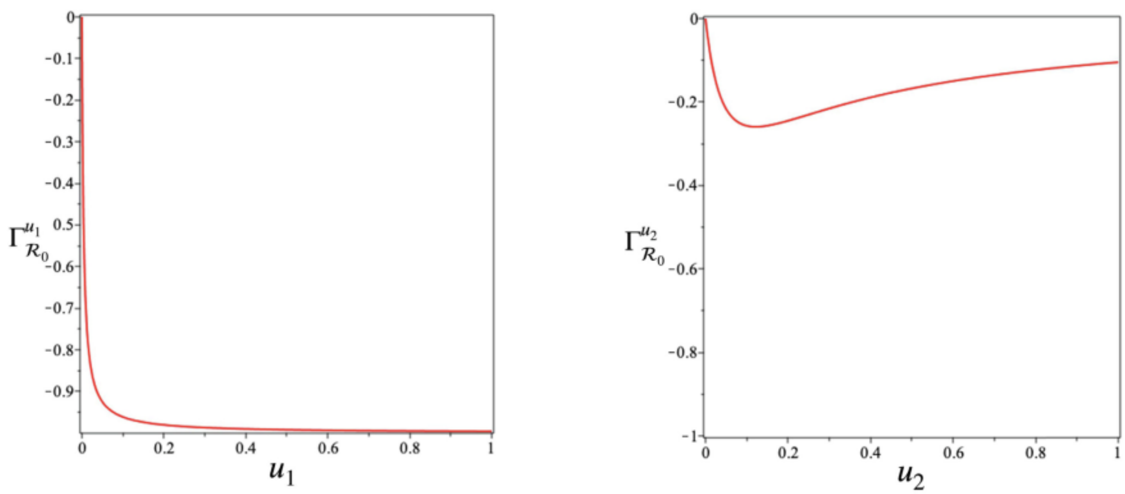
5.2. *Sensitivity analysis on the dynamical system*

5.2.1. *Local sensitivity analysis*

In this section, we perform sensitivity of the dynamical system considering the chosen parameters which include: the media campaign u_1, loss of awareness rate α, case detection u_2, maximum recovery rate $\rho_{\max}$, saturation parameter b, and infection rate β. To conduct this analysis, we use a recipe as explained in [58]. Let

Table 3 Elasticity of $\mathcal{R}_0$ considering the parameters using the best-fit parameter in Table 2.

Parameter	$\Gamma^{s}_{\mathcal{R}_0}$	Parameter	$\Gamma^{u_2}_{\mathcal{R}_0}$
θ_h	1	μ_h	−0.99
μ_v	−1	η	0
δ	3×10^{-4}	ρ_1	−0.52
$\rho_{\max}$	−0.26	u_1	−0.87
u_2	−0.22	α	−0.86
β	1	ξ	8.11×10^{-6}
p	−0.11	b	0



(a) (b)

Fig. 6 Dynamic of elasticity of $\mathcal{R}_0$ considering u_1 (left) and u_2 (right).

$$z_1 = \frac{\partial S}{\partial u_1},\ z_2 = \frac{\partial A}{\partial u_1},\ z_3 = \frac{\partial E}{\partial u_1},\ z_4 = \frac{\partial I}{\partial u_1},\ z_5 = \frac{\partial H}{\partial u_1},\ z_6 = \frac{\partial R}{\partial u_1},$$

represent the sensitivity of S, A, E, I, H, and R considering u_1, respectively. Hence, we obtain

$$\frac{\partial z_1}{\partial t} = \frac{\partial}{\partial t}\frac{\partial S}{\partial u_1} = \frac{\partial}{\partial u_1}\frac{\partial S}{\partial t}.$$

Because $\frac{\partial S}{\partial t}$ in system (4) is a function depending on other variables, using the chain rule achieves

$$\frac{\partial z_1}{\partial t} = \frac{\partial \frac{\partial S}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial S}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial S}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial S}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial S}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial S}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial S}{\partial t}}{\partial R} z_6.$$

Using a similar approach, we can derive the equation of sensitivity of other variables to u_1. Hence, the complete system for the sensitivity of dynamical system is expressed as:

$$\begin{aligned}
\frac{\partial z_1}{\partial t} &= \frac{\partial \frac{\partial S}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial S}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial S}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial S}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial S}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial S}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial S}{\partial t}}{\partial R} z_6,\\
\frac{\partial z_2}{\partial t} &= \frac{\partial \frac{\partial A}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial A}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial A}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial A}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial A}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial A}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial A}{\partial t}}{\partial R} z_6,\\
\frac{\partial z_3}{\partial t} &= \frac{\partial \frac{\partial E}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial E}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial E}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial E}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial E}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial E}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial E}{\partial t}}{\partial R} z_6,\\
\frac{\partial z_4}{\partial t} &= \frac{\partial \frac{\partial I}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial I}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial I}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial I}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial I}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial I}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial I}{\partial t}}{\partial R} z_6,\\
\frac{\partial z_5}{\partial t} &= \frac{\partial \frac{\partial H}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial H}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial H}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial H}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial H}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial H}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial H}{\partial t}}{\partial R} z_6,\\
\frac{\partial z_6}{\partial t} &= \frac{\partial \frac{\partial R}{\partial t}}{\partial u_1} + \frac{\partial \frac{\partial R}{\partial t}}{\partial S} z_1 + \frac{\partial \frac{\partial R}{\partial t}}{\partial A} z_2 + \frac{\partial \frac{\partial R}{\partial t}}{\partial E} z_3 + \frac{\partial \frac{\partial R}{\partial t}}{\partial I} z_4 + \frac{\partial \frac{\partial R}{\partial t}}{\partial H} z_5 + \frac{\partial \frac{\partial R}{\partial t}}{\partial R} z_6,
\end{aligned} \tag{19}$$

with an initial condition $z_i(0) = 0$ for $i = 1, 2, \ldots 6$. Therefore, to perform the sensitivity of the dynamical system considering u_1, we have to solve the following system of ODE:

1. Dengue model in system (4) with initial condition $S(0) = 6408450,\ A(0) = 273229,\ E(0) = 25,\ I(0) = 0,\ H(0) = 7,\ R(0) = 3878289$.
2. Sensitivity equation in system (19) with initial condition $z_i(0) = 0$ for $i = 1, 2, \ldots 6$.

The sensitivity analysis that we have conducted in this section is a local sensitivity analysis in which we have only examined the output when only one parameter (u_1) is changed. The sensitivity analysis on the dynamical system regarding $\alpha, u_2, \rho_{\max}, b$, and β is conducted similarly as explained above. Using the ODE solver in Maple, the result is demonstrated in Fig. 7 and 8.

Considering the results shown in Fig. 7, it can be observed that the number of infected people (I) is most sensitive to β, followed by $\alpha, u_1, u_2, \rho_{\max}$, and b, respectively. It can also be observed that increasing parameters β or α will significantly increase the number of infected individuals I, whereas increasing $u_1, u_2, \rho_{\max}$, or b will reduce the number of infected individuals I. The sensitivity of the I variable obtains its most sensitive value when an outbreak of H occurs. This is when $t = 100$ or during March 2020 on the incident data shown in Fig. 3. Furthermore, we also observe that the hospital capacity (which is represented by b) does not significantly change the number of $I(t)$. Our results in Fig. 7a and 7c confirm our elasticity analysis result. This indicates that the media campaign is more sensitive in reducing the spread of dengue, compared to detection intervention in Section 5.1.

The sensitivity of the dynamic of $H(t)$ considering $u_1, \alpha, u_2, \rho_{\max}, b$ and β is demonstrated in Fig. 8. The result is similar to that of Fig. 7, where β is the most sensitive parameter, followed by $\alpha, u_1, u_2, \rho_{\max}$, and b. We observed that the sensitivity of H considering u_2 was not always negative although it was positive at the beginning of the simulation, which was insignificant). This result indicates that increasing the number of case detections will increase the number of hospitalized individuals early on, but reduce the number later.

5.2.2. Global sensitivity analysis

To obtain a comprehensive understanding of the influential parameters of the model, besides the numerical approach of plotting the level set of reproduction numbers against the several parameters of interests to perform sensitivity analysis, we also perform a global sensitivity analysis on the dynamic of infected and hospitalized individuals using the combination of Latin Hypercube Sampling and Partial Rank Correlation Coefficient. Ten thousand samples were simulated, and the PRCC values were measured. The results were presented in Fig. 9 and 10. Considering these figures, we determine the influential parameters by measuring against an increasing number of infected and hospitalized individuals. This aims to determine the parameters with an increasing number of infected individuals in more sampling data.

Fig. 9 shows the control parameters (u_1 and u_2) and mosquito death rate (μ_v). The transmission-related parameters (β_h and β_v) are the most influential parameters, where the first three have a negative relationship, and the latter has a positive relationship. The results are realistic because the control u_2 speeds up the detection of the infected individuals. Therefore, they are moved to hospitals, decreasing the number of infected individuals. Furthermore, an increase in the level of awareness (u_1) contributes to a reduction in the number of infected individuals.

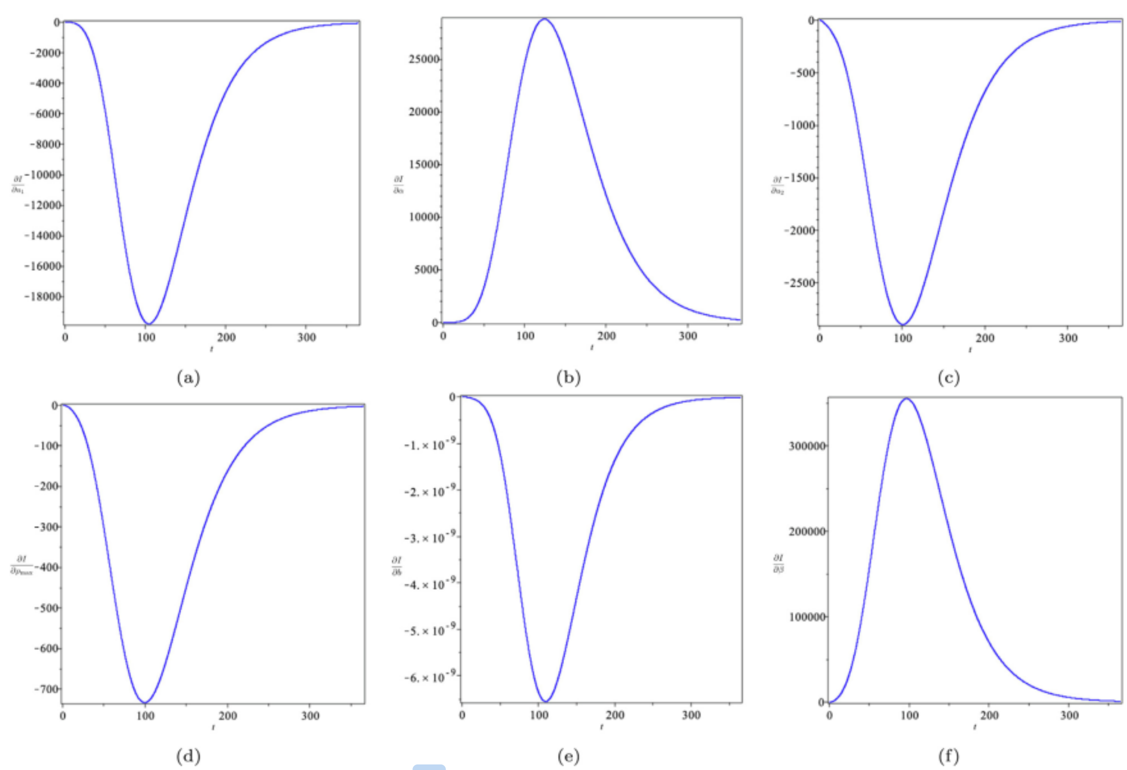


Fig. 7 Dynamical sensitivity of I respect to $u_1, \alpha, u_2, \rho_{\max}, b$ and β (from (a) to (f), respectively).

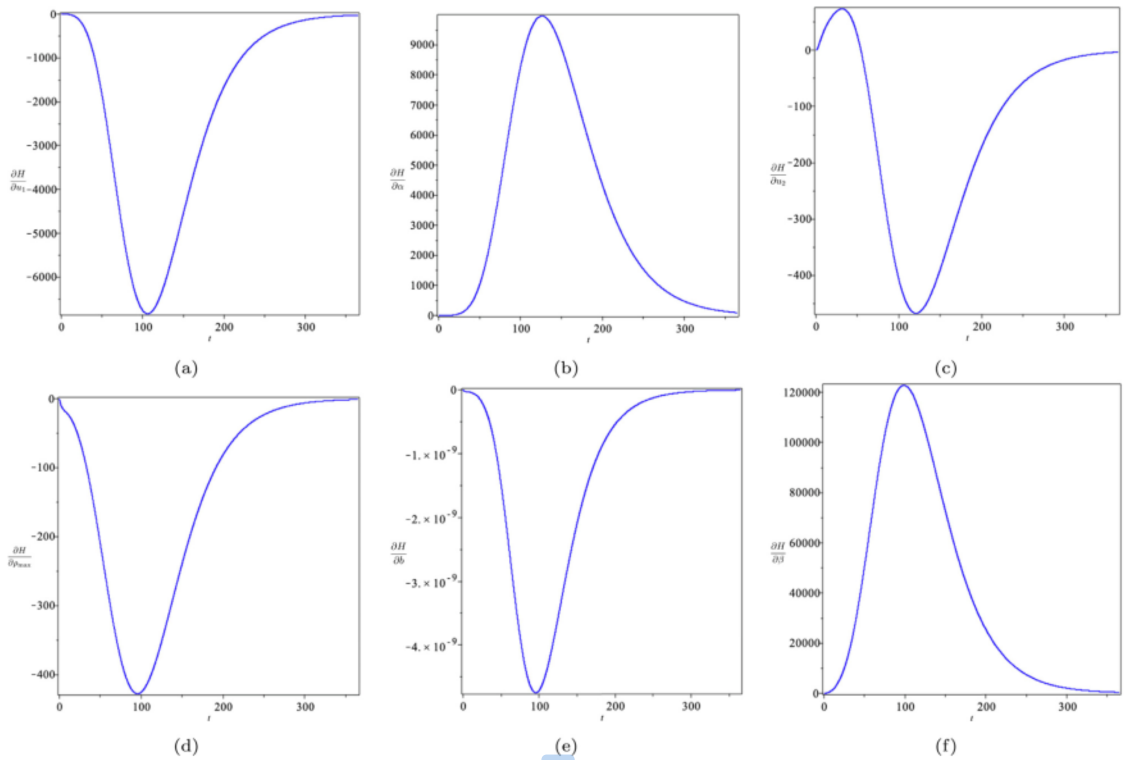


Fig. 8 Dynamical sensitivity of H respect to $u_1, \alpha, u_2, \rho_{\max}, b$ and β (from (a) to (f), respectively).

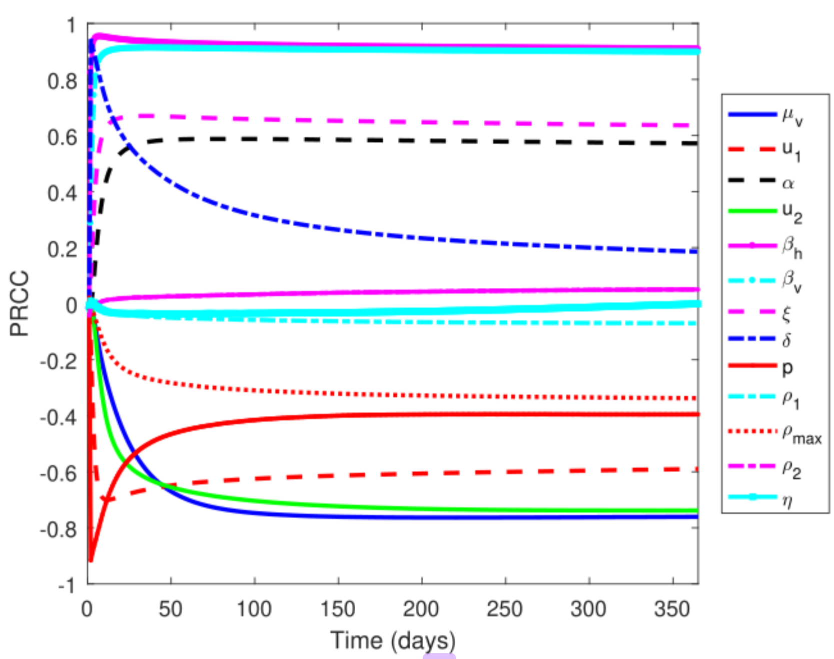


Fig. 9 PRCC values when measured against the increasing number of infected individuals.

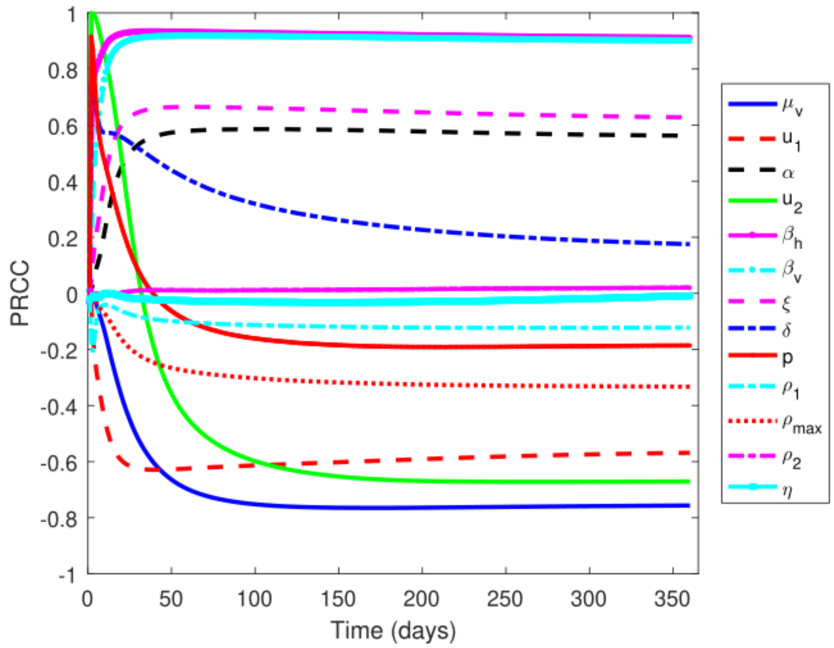


Fig. 10 PRCC values when measured against the increasing number of hospitalized individuals.

We also perform a global sensitivity analysis against the increasing number of hospitalized individuals, and the results are shown in Fig. 10. We realize that the control parameters governing an increase in the number of hospitalized individuals are similar to that of the infected individuals. Considering the early period, the control parameter (u_2) initially has a positive relationship but has a negative relationship later on. This indicates that an increase in the detection rate leads to more hospitalized cases early on, but fewer such cases later. The number of infected individuals decreases because a number of them can be detected early on, and this may explain why the control parameter u_2 has a negative relationship later on.

6. Conclusion

In this study, we formulate a mathematical model for a dengue control program. The model was constructed as a system of ODE, where the human population is divided into six compartments, and mosquitoes are divided into two compartments. The model included two forms of intervention: a media campaign to increase community awareness on dengue and case detection to send infected individuals to the hospital. We show that our model has a unique disease-free equilibrium and is always locally asymptotically stable when the basic reproduction number is less than one. The existence and local stability of the endemic equilibrium were examined analytically and numerically. Considering a simple case with no saturation on the treatment rate of hospitalized individuals, we observe that there is always a unique endemic equilibrium when the basic reproduction number is larger than one. From this analysis, we can conclude that it is important to achieve a condition $\mathcal{R}_0 < 1$ in order to achieve a dengue-free situation in the community.

The proposed model is used to understand the dynamic of dengue in Jakarta. Hospitalization data in Jakarta during 2020 was used to calibrate the model by finding the best-fit parameter for the model. Considering the basic reproduction number analysis using the best-fit parameter obtained from the parameter estimation result, we observe that media campaign is more sensitive than case detection. In addition, we observe that the case detection on its own is insufficient to eliminate dengue from Jakarta, and should be combined with media campaigns. For example, in order to control dengue transmission in Jakarta, the government should always update the increased number of hospitalized individuals to the public through electronic media, social media, or other media. With this update, education to the community about preventing dengue infection and a healthy lifestyle could also be considered. Sensitivity analysis on the dynamic of non–hospitalized and hospitalized individuals (local and global sensitivity analysis) shows that media campaign and case detection achieve their maximum sensitivities in the period of dengue outbreak. Owing to the maximum quality of treatment and hospital capacity, we observe that case detection does not always provide a better result when the intensity of case detection is given in a larger value. There is a critical value of case detection, where the impact of this intervention can still significantly reduce the basic reproduction number.

A number of research has been conducted to understand the effects of awareness on dengue transmission dynamics. Mishra and Gakkhar [59] formulated dengue mathematical model with awareness and found that the use of large amount of mosquito control, host awareness or its combination aid in controlling dengue transmission. Zheng et al [60] formulated a two-strain dengue model with awareness to investigate the effects of awareness and and mosquito control on dengue transmission dynamics. They found that the both controls are required to reduce the number of dengue cases. Furthermore, Research by Ndii analyzed the effects of vector control, vaccination, and media on dengue transmission dynamics and found that the efficacy of media in raising individual awareness determine the reduction in the number of dengue cases [61]. Aldila also conducted a research to examine the effects of media awareness on dengue transmission dynamics [62]. It is found that a combination of media campaigns and fumigation can prevent an increase in the number of infected individuals. Generally, previous research showed that individual awareness in combination with other intervention, which are vaccination and vector controls, can significantly reduce dengue transmission. Different to previous research, this research investigate the impact of social awareness, cases detection and its relation to hospital capacity in reducing dengue transmission. Interestingly, the results show that the case detection is not influential factor in reducing dengue transmission. A main factor to reduce dengue transmission is increasing individual's awareness, which is similar to the previous research.

Although our model already discusses some complexity of dengue transmissions, such as awareness, case detection, and hospitalization, the model can still be developed further by including other important factors such as human mobility [63], multi-strain infection [64],vaccination [65], the impact of seasonal factor [33], coinfection with other diseases [66], etc. Therefore, future research needs to consider these essential factors to get a better insight into the effort of the dengue control program.

7. Data availability

We thank to The Health Office of Jakarta City for providing us with the dengue data. The data that support the findings of this study are available from the corresponding author, D. A., upon reasonable request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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