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Mathematical modeling of COVID-19 epidemic with effect of awareness programs

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A B S T R A C T

Severe acute respiratory syndrome coronavirus 2 (SARS-COV-2) is a novel virus that emerged in China in late 2019 and caused a pandemic of coronavirus disease 2019 (COVID-19). The epidemic has largely been controlled in China since March 2020, but continues to inflict severe public health and socioeconomic burden in other parts of the world. One of the major reasons for China's success for the fight against the epidemic is the effectiveness of its health care system and enlightenment (awareness) programs which play a vital role in the control of the COVID-19 pandemic. Nigeria is currently witnessing a rapid increase of the epidemic likely due to its unsatisfactory health care system and inadequate awareness programs. In this paper, we propose a mathematical model to study the transmission dynamics of COVID-19 in Nigeria. Our model incorporates awareness programs and different hospitalization strategies for mild and severe cases, to assess the effect of public awareness on the dynamics of COVID-19 infection. We fit the model to the cumulative number of confirmed COVID-19 cases in Nigeria from 29 March to 12 June 2020. We find that the epidemic could increase if awareness programs are not properly adopted. We presumed that the effect of awareness programs could be estimated. Further, our results suggest that the awareness programs and timely hospitalization of active cases are essential tools for effective control and mitigation of COVID-19 pandemic in Nigeria and beyond. Finally, we perform sensitive analysis to point out the key parameters that should be considered to effectively control the epidemic.

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1. Introduction

In late 2019, an outbreak of novel coronavirus disease 2019 (COVID-19) caused by a severe acute respiratory syndrome coronavirus (SARS-CoV-2) was first reported in China (Li et al., 2020; Wu, Leung, & Leung, 2020; Lin et al., 2020a; WHO, 2020a, 2020b; CDC, 2020; Nishiura et al., 2020; Zhao et al., 2020a; Musa, Gao, Zhao, et al., 2020). The outbreak later inflicted more than 200 countries and became a pandemic (WHO, 2020a, 2020b; CDC, 2020). The outbreak has largely been controlled in China and some countries since March 2020, but still remains a serious public health and socio-economic problem in other countries/regions e.g., America, Europe, Middle East, and Africa, resulting hundred thousands of fatalities (Gilbert et al., 2020; Musa, Zhao, Wang, et al., 2020; Zhou et al., 2020). According to the World Health Organization (WHO), as of January 25, 2021, the COVID-19 pandemic affected 98,794,942 people including 2,124,193 associated deaths worldwide, see https://covid19.who.int/ (WHO, 2020a, 2020b). Some of the symptoms of COVID-19 are similar to the other two coronaviruses (i.e., MERS-CoV and SARS-CoV) which include fever, coughing, difficulty in breathing, Pneumonia in severe cases and common cold (CDC, 2020; Li et al., 2020; Tang et al., 2020; Wu, Leung, & Leung, 2020). The virus can be transmitted from person-to-person via small droplets of an infected individual when sneezing, coughing or via close contact (CDC, 2020; Li et al., 2020; Musa, Zhao, Wang, et al., 2020; Wang et al., 2020; Wu, Leung, & Leung, 2020). The incubation period of COVID-19 is estimated to vary from two to fourteen days (Li et al., 2020; Musa, Gao, Zhao, et al., 2020; Musa, Zhao, Wang, et al., 2020; Tang et al., 2020; Wu, Leung, & Leung, 2020) which is regarded as the minimum period for an exposed individual to be quarantined (Backer et al., 2020; Tang et al., 2020).

Nigeria, the most populous country in sub-Saharan Africa, whose health care system does not provide basic and regular health services adequately for its citizens even in normal situations; hit by the double burden from COVID-19 and other infectious and non-infectious diseases (NCDC, 2020). Notwithstanding, in its trying to tackle the pandemic situation in the country, the Nigeria government considered some basic measures prior to the first case detection in 27 February 2020 and still modifying them according to WHO recommendations (WHO, 2020a, 2020b; Gilbert et al., 2020; NCDC, 2020). These measures include improving health institutions, creation of isolation and quarantine centers to treat/isolate COVID-19 patients, borders and schools closures, creation of awareness and enlightenment programs at different levels and in different methods, and resource support mobilization from different groups to assist the community, especially the most vulnerable individuals, in order to facilitate the control and prevention of the disease at different levels. The total number of active cases and deaths of COVID-19 in Nigeria recorded by the Nigeria Centre for Disease Control (NCDC) as of January 25, 2021 were 122,996 and 1,507, respectively (NCDC, 2020).

Currently, there is no safe and effective vaccine or antiviral treatment for use against the COVID-19 infection. Therefore, the control of COVID-19 are currently directed primarily on applying set of non-pharmaceutical interventions (NPIs) measures, as well as use of treatments to improve the immune systems of infected individuals (CDC, 2020; WHO, 2020a, 2020b). The fact that the management and mitigation efforts to halt or reduce the spread of the COVID-19 pandemic are largely focused on implementing non-pharmaceutical interventions (NPI), such as social or physical distancing, community-wide lock-down, contact tracing, dissemination of health education knowledge on COVID-19 (awareness programs), quarantine of suspected cases, isolation of confirmed cases and use of face-masks (18, 19).

Recently, there were several epidemiological modeling studies that have been done to explore the transmission dynamics of COVID-19 in human population (Chen et al., 2020; Eikenberry et al., 2020; Gilbert et al., 2020; Iboi, Sharomi, et al., 2020; Lin et al., 2020a; Musa, Gao, Zhao, et al., 2020; Ngonghala et al., 2020;Tang et al., 2020·Musa, Zhao, Wang, et al., 2020; ; Wu, Hao et al., 2020; Wu, Leung, & Leung, 2020; Zhao et al., 2020a; Ma, 2020). Wu, Hao et al., (2020) employed a simple Susceptible-Exposed-Infectious-Recovered (SEIR) based model to forecast the potential of the COVID-19 to spread in China and beyond. They estimated the reproduction number (R_0) at $2{\cdot}68\,(95\%\,\mathrm{CI}: 2{\cdot}47-2{\cdot}86)$ and epidemic doubling time at $6{\cdot}4$ days $(95\%\ \mathrm{CI}:\ 5{\cdot}8-7{\cdot}1)$ indicating the exponential growing nature of the COVID-19 outbreak. Tang et al. (2020) developed and analyzed a deterministic model which incorporates quarantine and hospitalization to estimate the transmission risk of the COVID-19 and its implication for public health interventions. Their model was further extended by Ngonghala et al. (2020) by dividing infectious compartment into two essential compartments of hospitalized or isolated individuals and those in intensive care units to assess the impact of NPI on curtailing the spread of COVID-19 pandemic. Musa, Zhao, Wang, et al. (2020) proposed a deterministic model to study the transmission dynamics of COVID-19 with effect of different quarantine measures and to examine the role of some key epidemiological parameters for control measures. They showed that the contact and recovery rates from asymptomatically infected individuals are the key parameters for effective control of the COVID-19 outbreak in Wuhan indicating the importance of timely quarantine and hospitalization to mitigate the epidemic. Memon et al., 2021 formulated a new COVID-19 model of deterministic type to assess role of quarantine and isolation for effective control of the epidemic in Pakistan. They carried out theoretical analysis of the model with discussion of existence, uniqueness, bounded-ness and equilibria of the model. Their estimated value for R_0 was about 1.31 which indicates persistence of the epidemic in the country. Based on real data for active cases in the country, they suggested some increase in the quarantine period as the effective tool to fight with the ongoing epidemic of COVID-19. Lin et al. (2020a) designed a conceptual model for the COVID-19 outbreak in Wuhan which incorporates individual behavioral reaction and governmental actions (e.g., holiday extension, travel restriction, hospitalization and quarantine). They computed the possible future trends and the reporting ratio of the virus. Their model captures possible course of the COVID-19 outbreak, and sheds light on understanding the patterns of the outbreak. Eikenberry et al. (2020) designed a mechanistic model to study the potential impact of the use of face-masks by the public to curtail the spread of the COVID-19 pandemic. Their results suggest that the use of face masks by public is potentially of high significance in curtailing the burden of the pandemic. The community-wide benefits are likely to be greatest when face masks are used in conjunction with other non-pharmaceutical practices (such as social or physical distancing), and high universal adoption and compliance.

In the current study, with reference to the aforementioned studies (Chen et al., 2020; Eikenberry et al., 2020; Gilbert et al., 2020; Iboi, Sharomi, et al., 2020; Lin et al., 2020a; Musa, Gao, Zhao, et al., 2020;; Musa, Zhao, Hussaini, et al., 2020; Musa, Zhao, Wang, et al., 2020;Ngonghala et al., 2020 ; Tang et al., 2020; Wu, Hao et al., 2020; Wu, Leung et al., 2020; Zhao et al., 2020b, 2020c), we designed a mechanistic model which incorporates different hospitalization measures for mild and severe cases to assess the effect of awareness programs on the dynamics of COVID-19 infection. We fit the epidemic curve using Nigeria COVID-19 cases report published by NCDC, accessed via https://covid19.ncdc.gov.ng/, and estimate some control parameters for COVID-19 epidemic in Nigeria and beyond. Our simulation results offer insights into the trends of COVID-19 epidemic in Nigeria, and assess or evaluate the effect of awareness programs, as well as draw useful guidelines for the design of control and prevention strategies. Our model framework can be applied to other countries, or be built into one multiple-patch model for modeling multiple countries context. This paper is organized as follows. The epidemic model is developed and analyzed in sections 2 and 3, respectively. In section 4, model fitting and parameter estimation are conducted and analysis is presented. Sensitivity analysis is presented in section 5. Section 6 present detailed discussion of the research study conducted in the present work.

2. Materials and methods

2.1. Epidemic data

The time series case data of the COVID-19 are extracted from the Nigeria Centre for Disease Control (NCDC) (NCDC, 2020) from March 29 to June 12, 2020. All cases are laboratory confirmed following the case definition by the NCDC situation report. Clinical diagnosis of suspected individuals was used as the criterion for confirmed cases since February 2020 (NCDC, 2020). The confirmed case is defined as the individual whose real-time reverse transcription polymerase chain reaction (rRT-PCR) result turned out to be positive.

2.2. Epidemic model

A new deterministic epidemic model is developed based on the standard SEIR model to study the transmission dynamics of COVID-19 outbreak. We split the total human population at time t, denoted by $N(t)$, into the mutually exclusive compartments of aware susceptible $S_a(t)$ (individuals who are aware of the disease and follow the preventive health measures), unaware susceptible $S_u(t)$ (individuals who are unaware of the disease and do not follow the preventive health measures), exposed $E(t)$, asymptomatically infectious $A(t)$, symptomatically infectious (consist of those having mild and severe symptoms) $I(t)$, mild hospitalized $H_m(t)$, severe hospitalized (individuals who are isolated in the hospital such as those in ICU or special clinics), and recovered $R(t)$ individuals. Thus, we have

$$N(t) = S_a(t) + S_u(t) + E(t) + A(t) + I(t) + H_m(t) + H_s(t) + R(t)$$

It is worth knowing that our model did not capture birth and death rates due to the relative short period of the epidemic, which started in early 2020 in Wuhan, China. Our model considers person-to-person mode of transmission as the potential transmission route and ignored other routes due to their less impact in community transmission. The model flow diagram is shown in Fig. 1, and the state variables and the model parameters (all positive) are summarized in Table 1. Our model equations are given by following nonlinear system of ordinary differential equations:

$$\frac{dS_a}{dt} = -\frac{\alpha\beta S_a(\sigma A + I)}{N} + \nu S_u,$$

$$\frac{dS_u}{dt} = -\frac{\beta S_u(\sigma A + I)}{N} - \nu S_u,$$

$$\frac{dE}{dt} = \frac{\beta(\sigma A + I)(\alpha S_a + S_u)}{N} - \theta E,$$

$$\frac{dA}{dt} = k\theta E - \eta_a A,$$

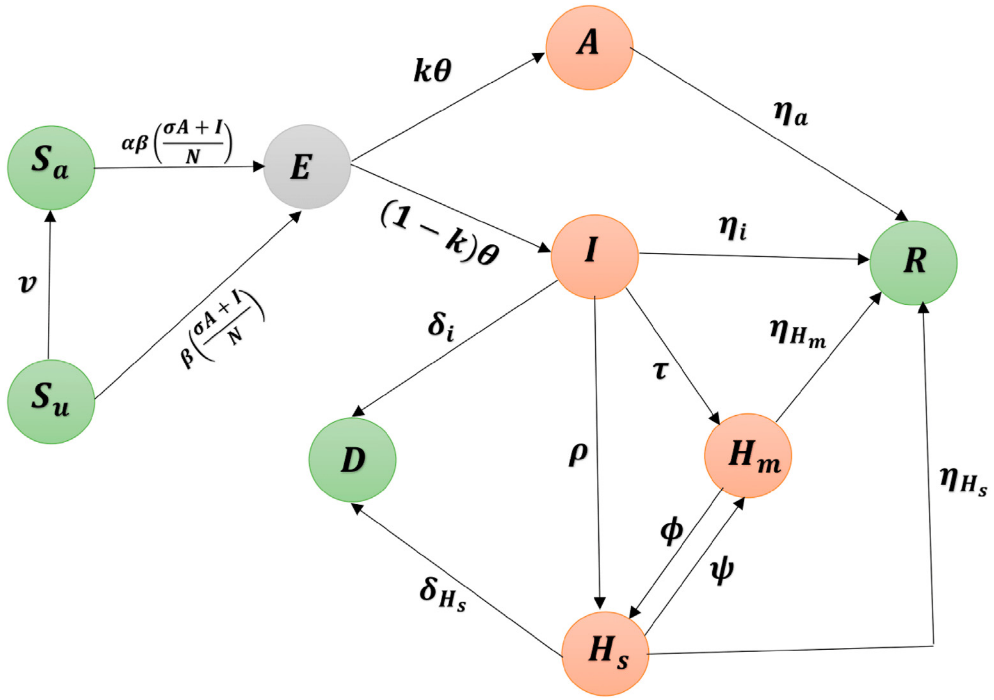

Fig. 1. The schematic diagram of the COVID-19 model, in Eqn (1), with awareness programs. The non-infected compartments are represented in green color, the compartment in gray denotes the exposed individuals, while the infected compartments are portrayed in pink color.

Table 1
Interpretation of the state variables and parameters used in the model (1).

Variable	Description
N	Total human population
S_a	Aware susceptible individuals
S_u	Unaware susceptible individuals
E	Exposed individuals, those who are in the latent period
A	Asymptomatically infectious individuals
I_m	Symptomatically infectious individuals
H_m	Hospitalized/isolated individuals with mild symptoms
H_s	Hospitalized/isolated individuals with severe symptoms
R	Recovered humans
D	Deceased humans
Parameter	
β	Community transmission or successful contact rate
α	Modification parameter for decrease on infectiousness in S_a
σ	Infectiousness factor for asymptomatic individuals
ν	Rate at which unaware susceptible will become aware about the disease
θ	Progression rate
k	Fraction of infections that become asymptomatic
$\tau(\rho)$	Hospitalization rates from I to H_m (H_s)
ψ	Rate at which the hospitalized individuals move from mild to severe isolation
φ	Rate at which the hospitalized individuals move from severe to mild isolation
$\delta_j(j = i, H_s)$	COVID-19 induced death rates
$\eta_l(k = a, i, H_m, H_s)$	Recovery rates

$$\frac{dI}{dt} = (1-k)\theta E - (\eta_i + \tau + \rho + \delta_i)I,$$

$$\frac{dH_m}{dt} = \tau I + \psi H_s - (\eta_{H_m} + \varphi)H_m,$$

$$\frac{dH_s}{dt} = \rho I + \varphi H_m - (\eta_{H_s} + \psi + \delta_{H_s})H_s,$$

$$\frac{dR}{dt} = \eta_a A + \eta_i I + \eta_{H_m} H_m + \eta_{H_s} H_s,$$

$$\frac{dD}{dt} = \delta_i I + \delta_{H_s} H_s.$$

In particular, the term $\frac{\beta(\sigma A+I)}{N}$ is the force of infection of the COVID-19 model (1), and all the remaining parameters are defined in Table 1. To keep tabs on the COVID-19-related deaths (required for model calibration with cumulative death-related data for COVID-19, and for quantifying and predicting the public health impact or burden of disease), we set the state variable $D(t)$ within the above proposed model to measure the number of COVID-19-deceased individuals.

3. Qualitative analysis

3.1. Disease-free equilibrium and basic reproduction number

In the absence of the infection (i.e., $S_u = E = A = I = H_m = H_s = R = D = 0$), the model (1) has a disease-free equilibrium (DFE), which is given by.

$$\Upsilon^0 = \left(S_a^0, S_u^0, E^0, A^0, I^0, H_m^0, H_s^0, R^0, D^0\right) = \left(S_a^0, 0, 0, 0, 0, 0, 0, 0, 0\right)$$

which is feasible. Thus, local stability of the equilibrium Υ^0 can be established in terms of the threshold value known as the basic reproduction number (R_0): a potential quantity which determines whether a disease can invade a population. Hence, R_0 is computed using the next generation matrix technique proposed in (van den Driessche & Watmough, 2002). It represents the number of secondary COVID-19 cases that would be generated by a typical primary case if placed into a completely susceptible population (van den Driessche & Watmough, 2002; Agusto et al., 2015; Diekmann et al., 1990; Musa, Zhao, Gao, et al., 2020; van den Driessche, 2017; Lin et al., 2020b; Zhao et al., 2020d; Musa et al., 2019).

Thus, the equation for R_0 is given by

$$R_0 = \rho^*\left(FV^{-1}\right) = \frac{\alpha\beta\sigma k}{\eta_a} + \frac{\alpha\beta(1-k)}{q_1}, \tag{2}$$

where $q_1 = \eta_i + \tau + \rho + \delta_i$, $q_2 = \eta_{H_m} + \varphi$, $q_3 = \eta_{H_s} + \psi + \delta_{H_s}$, $S_a^0 = N^0$ (i.e., at DFE $S_a^0 = N^0$ since we considered closed population) and ρ^* (spectral radius) is defined as the maximum of the absolute values of the eigenvalues of the matrix FV^{-1}.

Hence, the result given below follows Theorem 2 of (van den Driessche & Watmough, 2002).

Theorem 3.1. *The DFE, Υ^0, of the model (2.1), is locally-asymptotically stable (LAS) if $R_0 < 1$, and unstable if $R_0 > 1$.*

Thus, the epidemiological implication of the above theorem is that a small influx of COVID-19 cases will not generate a large COVID-19 outbreaks if the R_0 is below unity.

3.2. Model fitting and parameter estimation

Validation of a newly proposed epidemiological model is one of the crucial process to examine a disease's transmission dynamics. Availability of real data for the underlying disease greatly helps to complete this task of validation, these data also assist to get best values of some unknown biological parameters involved in the model. Therefore, we have carried out this approach via nonlinear least-squares curve fitting method with the help of a routine "*fminsearch*" function from the MATLAB Optimization Toolbox. Based upon the strategy, if a theoretical model $t := \Xi(t, p_1, p_2, \ldots, p_n)$ is obtained which depends on a few unknown parameters $p_1, p_2, \ldots, p_n$ and a sequence of actual data points $(t_0, y_0), \ldots, (t_j, y_j)$ is also at hand then the goal is to achieve values of the parameters for which the computed error, attains a minimum.

$$\Sigma := \sqrt{\sum_{i=0}^{j} (\Xi(t, p_1, p_2, \ldots, p_n) - y_i)^2} \quad (3)$$

There are 17 biological parameters associated with the proposed model. Some of them have been obtained from available literature whereas the, rest have been best fitted. As can be seen in Table 2, the parameters $\nu, \alpha, \beta, \sigma, \theta, k, \eta_a, \eta_i$, and ψ have been best fitted using the aforementioned strategy while the parameters $\eta_{H_m}, \eta_{H_s}, \delta_i, \delta_{H_s}, \mu, \tau, \rho$, and φ have been used from available literature as cited. Based upon the available information, the initial conditions for the state variables of the proposed model are chosen to at $S_a(0) = 130000000$, $S_u(0) = 76000000$, $E(0) = 22$, $A(0) = 10$, $I(0) = 111$, $H_m(0) = 5$, $H_s(0) = 0$, $R(0) = 0$, and $D(0) = 0$. The choice of initial conditions, available and fitted biological parameters yielded the average absolute relative error of magnitude $1.2861e-01$ which is reasonably small enough. Moreover, real COVID-19 Nigerian cases and the fitted curve have been shown in (a) plot Fig. 2 wherein it is observed that the model fits the real cases well enough while the residuals are also obtained in (b) plot of Fig. 2 which show a justified trend of the obtained residuals as they are scattered even below and above the horizontal line (blue in color). The residuals are defined in Equation (3). Whenever the reported data come under the fitted curve then residues will be shown below that horizontal line (blue color line in (b) part of Fig. 2) and similarly when the reported data lie above the fitted curve then residues will be shown above that horizontal line (blue color line in (b) part of Fig. 2). The numbers for residues show the vertical distance between reported data and fitted curve. Moreover, when such residues are observed to be scattered then the fitting is justified. In other words, if the residuals appear to behave randomly, it suggests that the model fits the data well. This is what happens in Fig. 2. The detailed explanation on fitting models on data with residual analysis can be found in Martin et al. (2017). Finally, the basic reproductive number (R_0) is estimated as $R_0 = 9.1235e-01$ ($95\%CI$: $5.8725e-02 - 2.8728$) using the parameters presented in Table 2. This result is largely consistent with previous estimate on the basic reproduction number (R_0) in Africa (Musa, Zhao, Wang, et al., 2020). Subsequently, the R_0 value will increase (i.e., $R_0 = 2.98$) if all the awareness related parameters are removed; indicating the positive impacts of awareness programs on curtailing the spread of COVID-19 pandemic in Nigeria and beyond.

4. Numerical simulations

In this section, the effect of awareness programs on the dynamics of COVID-19 is explored by simulating the awareness related parameters of the model (1) over the time interval $[0, 300]$. The proposed model (1) is simulated under three scenarios given below while using the initial conditions and parameters given in subsection 3.2. The step size during simulations is taken to be $h = 10^{-2}$ where $Nh = 300$. Moreover, simulations have been obtained with the help of ode23s solver in MATLAB software ('9.8.0.1323502 (R2020a)') running on 64 bit Windows OS having processor of Intel(R) Core(TM) i7-1065G7 CPU @ 1.30 GHz and installed memory (RAM) of 24.0 GB.

4.1. Scenario 1: effects of awareness programs

In Fig. 3, we consider the case when the dynamical features of the model (1) with varying values of control parameters over time interval 0 to 300 are shown. As expected, there is an increase of the number of systematically infected individuals

Table 2
Baseline values of the parameters used in the model (1).

Fitted parameter	Value (Range)	Units/remarks	Sources
ν	$1.73768e-02$ (0.01 – 0.5)	day^{-1}	fitted
α	3.06589e-01 (0.01–0.95)	day^{-1}	fitted
β	8.48007e-01 (0.599–1.68)	day^{-1}	fitted
σ	6.74971e-02 (0.04–0.6)	day^{-1}	fitted
θ	8.79588e-01 (0.05–0.95)	day^{-1}	fitted
k	1.63179e-02 (0–1)	day^{-1}	fitted
η_a	3.67068e-02 (1/28 - 1/3)	day^{-1}	fitted
η_i	9.17384e-03 (1/1000 - 1/3)	day^{-1}	fitted
ψ	1.69055e-01 (0.001–0.5)	day^{-1}	fitted
Parameter from the literature			
η_{H_m}	0.11624 (0 – 1)	day^{-1}	(Musa, Gao, Zhao, et al., 2020; Tang et al., 2020)
η_{H_s}	0.155 (0 – 1)	day^{-1}	(Musa, Gao, Zhao, et al., 2020; Tang et al., 2020)
δ_i	0.015 (0.01 – 0.05)	day^{-1}	(Iboi et al., 2020b; Tang et al., 2020)
δ_{H_s}	0.025 (0.01 – 0.05)	day^{-1}	(Iboi et al., 2020b; Musa, Gao, Zhao, et al., 2020)
μ	0.00005 (0.00003 – 0.00006)	day^{-1}	(Musa, Zhao, Gao, et al., 2020; Musa, Zhao, Wang, et al., 2020)
τ	0.1259 (0.09 – 0.51)	day^{-1}	(Musa, Gao, Zhao, et al., 2020; Tang et al., 2020)
ρ	0.13266 (0.001 – 0.5)	day^{-1}	(Tang et al., 2020)
φ	0.0341 (0.001 – 0.5)	day^{-1}	(Musa, Gao, Zhao, et al., 2020)

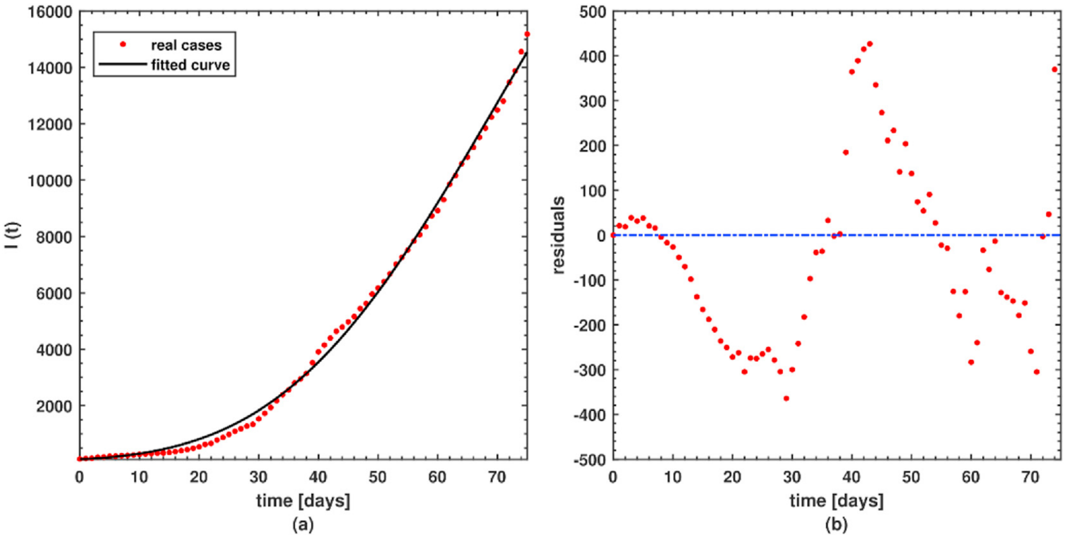

Fig. 2. (a) The daily COVID-19 cumulative cases time series in Nigeria from March 29 to June 12, 2020 with the best fitted curve from simulations of the proposed model and (b) the residuals for the best fitted curve.

with increase of the number of the key parameters (β, α, σ). Further, to explore the impact of the awareness program on the dynamical model described in equation (1), we conducted simple simulations, with multiple choices of these key parameters (β, α, σ). The simulation results in Fig. 3 agree with our theoretical analyses result, indicating that increasing the rate of awareness program may significantly reduce the rise in the number of COVID-19 cases in a population. In (a) plot of Fig. 3, it can be seen that a 2.6% decrease in value of β (community contact rate) can substantially decrease the level of infection. In plot (b) of Fig. 3, an increase of 6.52% in α (modification parameter for decrease on infectiousness on S_a) also decreases the number of infectious individuals. Similarly, 17.39% decrease in σ (infectiousness factor for asymptomatic individuals) decreases the infection's level by a small amount. In other words, our results emphasize the significance of awareness program as one of the potential strategies in combating the COVID-19 epidemic.

4.2. Scenario 2: model simulation results

Here, we consider the hypothetical scenario where COVID-19 begins to spread more rapidly in unaware susceptible area (unaware susceptible region) than in low prevalence area (aware susceptible region) where the outbreak could be eradicated faster likely due to following of common non-pharmaceutical control health measures recommended by the WHO, see Figs. 4 and 5 (a-d). The results indicate that lack of proper and constant awareness program of susceptible and exposed individuals could lead to a larger prevalence of COVID-19 especially in a country with already overwhelmed health care system such as Nigeria. This further illustrates that adequate awareness and enlightenment programs in a most vulnerable communities is a good way to fight against the disease especially in countries with poor health care systems.

4.3. Scenario 3: simulations for contour plots of the model

In this scenario (Fig. 6), we obtained some contour plots for the basic reproductive number, R_0, as a function of two different epidemiological parameters chosen from Table 1. Fig. 6 (a)–(f) indicates that the parameters $\beta, \theta, \varphi, \omega$ and ψ seems very significant (vital) and should be considered in mitigating the COVID-19 pandemic in Nigeria. In Fig. 6 (a), we showed that the basic reproduction number, R_0, increases with respect to the increase in α, and the β as expected. In Fig. 6 (b), we show that the basic reproduction number, R_0, increases with respect to the increase in α and σ. In Fig. 6 (c), decrease in β and increase in δ_i causes decrease in basic reproduction number, R_0. Similarly, in Fig. 6 (d), decrease in β and increase in ψ causes decrease in basic reproduction number, R_0. In Fig. 6 (e), decrease in β and increase in τ causes decrease in basic reproduction number, R_0. On the other hand, increase in k and σ causes increase in R_0, as depicted in Fig. 6 (f), respectively.

5. Sensitivity analysis

In this section, sensitivity analysis is carried out using the partial rank correlation coefficients (PRCCs) for ranking the significance of each parameter output through determining the target biological quantities/parameters, i.e., the basic reproduction number and the infection attack rate as response functions (see, Fig. 7) (Gao et al., 2016), to get insight into designing effective control measures or strategies to combat the epidemic.

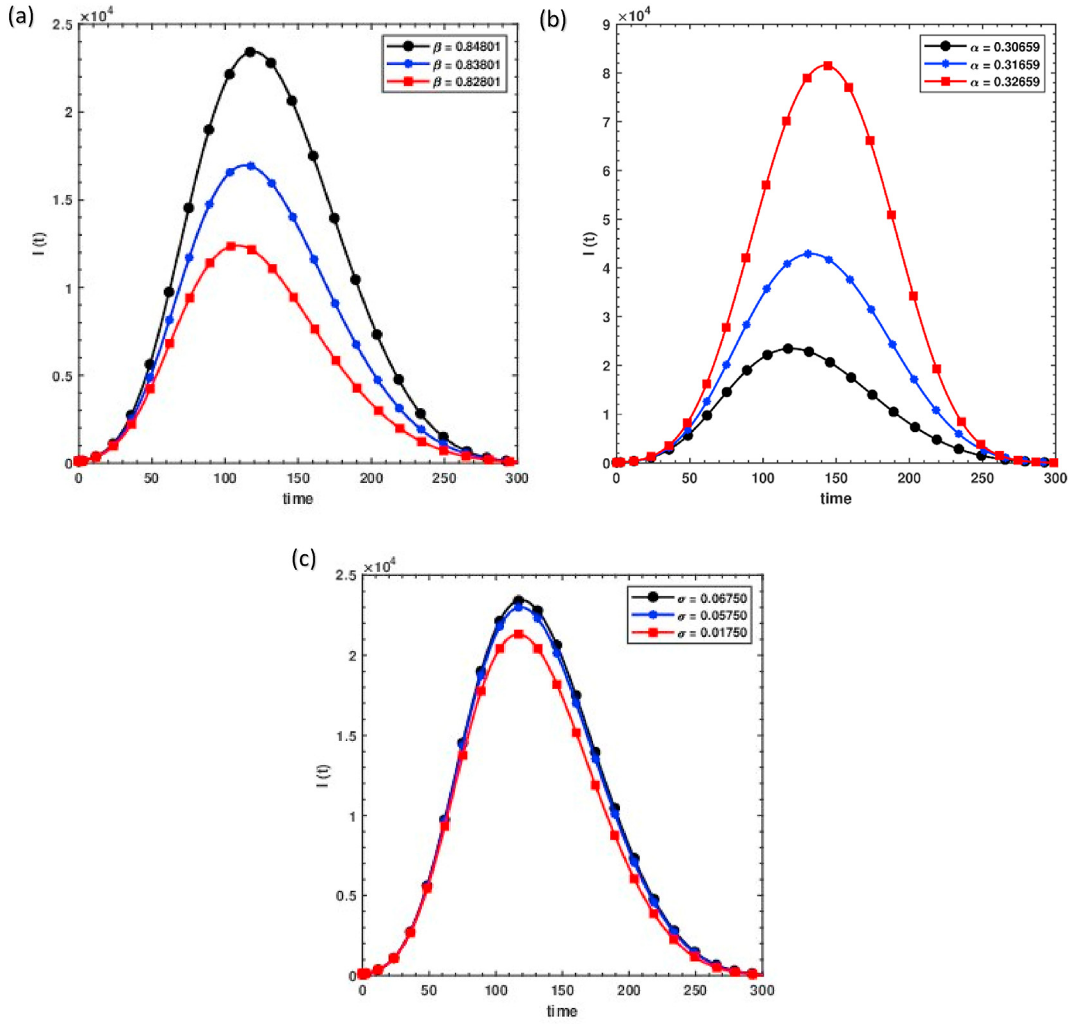

Fig. 3. Simulations of the model (1) for various awareness programs under control measures with varying values of (a) β (community contact rate), (b) α (modification parameter for deceased on infectiousness in S_a compartment), and (c) σ (infectiousness factor for asymptomatic individuals) while using the parameters' values given in Table 2.

Using the parameters' values given in Table 2, we performed 500 random simulations for each model parameter from uniform distributions. Each sub-model is simulated for each random parameter values to obtain the target epidemiological quantities. Thus, the PRCCs were computed between each parameter and target epidemiological quantities. In the current model, the PRCCs results revealed that the top ranked epidemiological parameters to effectively curtail the spread of the disease in order of preference are: (i) α followed by (ii) β and σ, then (iii) η_a. These parameters are directly linked to the awareness programs, and thus they should be prioritized to effectively control the COVID-19 pandemic in Nigeria.

6. Discussion

Since early 2020, the world has been facing a devastating COVID-19 pandemic, caused by SARs-CoV-2, which appeared in Wuhan, Hubei province of the Central China. The pandemic, which has rapidly spread to over 200 countries and territories, continues to inflict major public health and socioeconomic domain worldwide, including Africa. As of 30 July 2020, globally, the COVID-19 pandemic accounted for 16,812,763 laboratory confirmed cases, including 662,095 deaths, according to WHO (https://covid19.who.int/). Until recently few vaccines or antiviral treatment for use against the COVID-19 in humans were readily available (many are still under clinical investigations), most of the control interventions efforts are primarily based on the use of non-pharmaceutical interventions (NPIs), which include social or physical distancing, city or community lockdown, timely contact tracing, quarantine of suspected cases, isolation of laboratory confirmed cases, use of face-masks and the awareness campaigns for the general public. Nigeria, the most populated country in Africa, was also hit with the burden of the COVID-19 pandemic (Gilbert et al., 2020; Musa, Zhao, Hussaini, et al., 2020; Musa, Zhao, Wang, et al., 2020). Efforts are

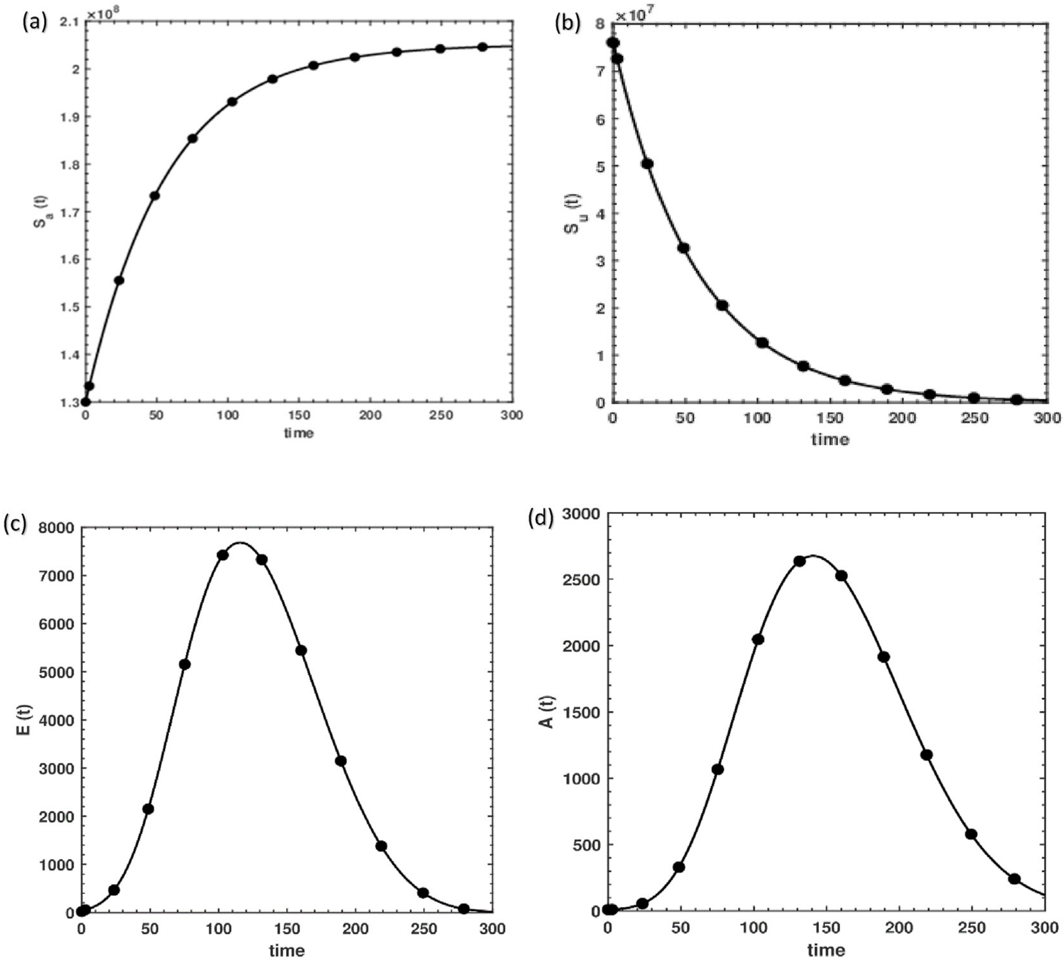

Fig. 4. Time series plots for the simulation of the model (1) showing the dynamical behaviour of the non-infectious compartments over time interval $[0, 300]$ while using the parameters' values given in Table 2.

currently being made to enlighten the public about the risk and the basic control health measures to curtail/reduce the spread of the virus. In this paper, we proposed a deterministic mathematical model to examine the dynamical features of the COVID-19 pandemic in Nigeria, and assessed the impacts of awareness programs in a society to effectively mitigate the epidemic. We parametrized the model using the COVID-19 data published by the Nigeria Centre for Disease Control (NCDC, accessed via https://covid19.ncdc.gov.ng/).

We performed model simulations in order to examine the effects of public awareness programs on the dynamics of COVID-19 transmission in Nigeria. Our simulations' result revealed that the parameters (β, α and σ) are the key (control) parameters that need special emphasis to curtail or reduce the burden of the COVID-19 pandemic in Nigeria and beyond. In particular, increasing the awareness level in a population by introducing effective enlightenment campaigns (to educate people on the impact of the pandemic and the implication of complying with non-pharmaceutical intervention strategies control measure in curtailing the spread of the COVID-19) can significantly reduce the infectiousness level in population. This could be achieved easily when the population acquire proper knowledge on how to (strictly) comply with non-pharmaceutical intervention strategies control measures. Moreover, nonlinear least-squares curve fitting method with the help of a routine *fminsearch* from MATLAB Optimization Toolbox was used for fitting the real cases of the COVID-19 cases in Nigeria between 27 February and 12 June 2020. The model (2.1) was fitted well to the daily reported cases.

Furthermore, our numerical simulation results revealed the key epidemiological/biological parameters of the model, which are α, β, σ, δ_i, k and τ, these parameters are essential to the model and should be prioritized in curtailing the spread of the COVID-19 pandemic in Nigeria and beyond. In addition, the PRCC for the sensitivity analysis also revealed that the top ranked parameters that should be emphasized for effective control of the epidemic are α, β, σ *and* η_a which are related to the awareness compartment, and they should be given priority to effectively control the COVID-19 outbreak. These results

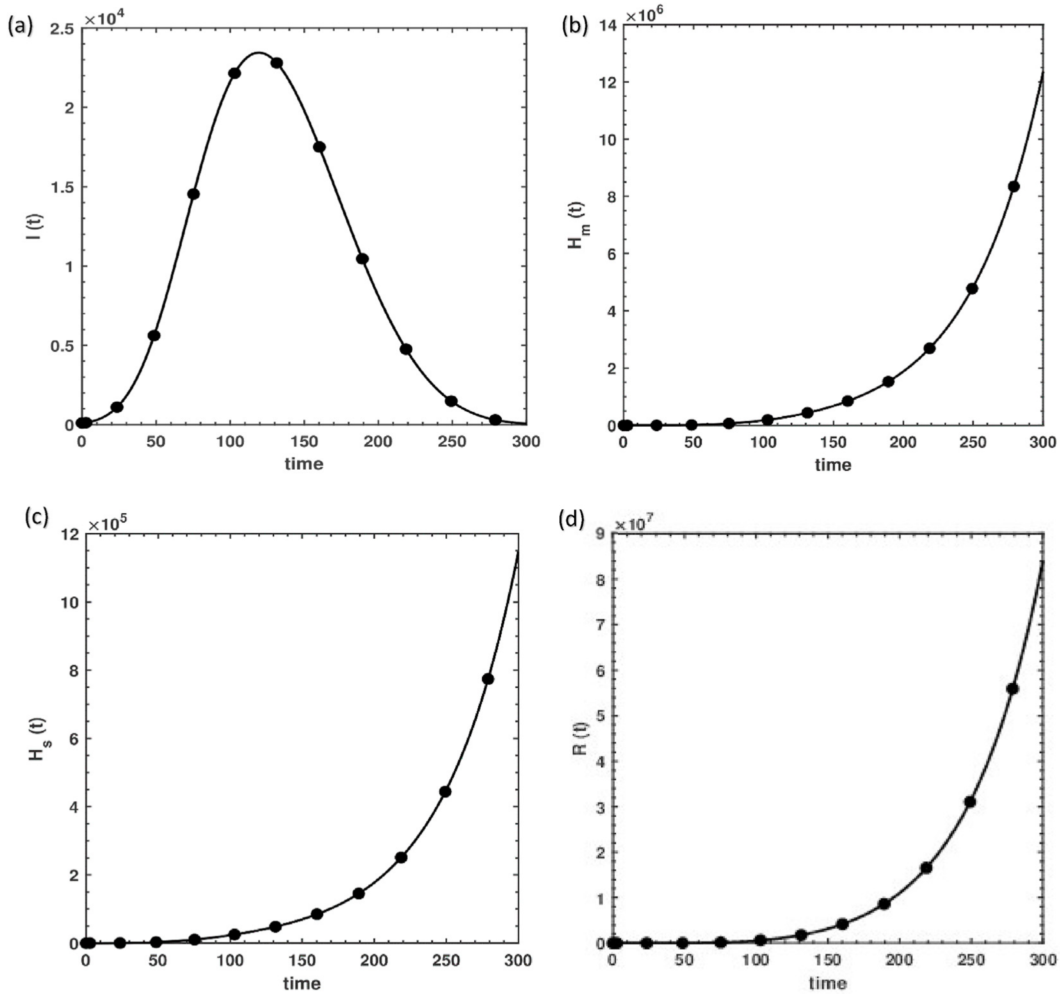

Fig. 5. Time series plots for the simulation of the model (1) showing the dynamical behaviour of the infectious compartments over time interval $[0, 300]$ while using the parameters' values given in Table 2.

indicate the impact of awareness programs on curtailing the spread of COVID-19 pandemic in Nigeria and beyond. Our future studies would include the use of Markov Chain Monte Carlo sampling technique for data fitting process to obtain the unknown biological parameters of the model with associated 95% credible intervals. Moreover, non-local time derivatives recently introduced in (Caputo, 1996; Atangana & Baleanu, 2016; Caputo & Fabrizio, 2015; Atangana, 2017) and successfully used in various real life situations (see, for instance (Atangana & Qureshi, 2019; Abro & Atangana, 2020; Ahmed et al., 2020; Atangana & Atangana, 2020; Baleanu et al., 2020; Naik et al., 2020; Ozair et al., 2020; Zarin et al., 2020), and will be taken under consideration to comprehend the dynamics of underlying epidemic in more detail.

Authors' contributions

SSM and DH conceived and carried out the study. SSM conducted the analyses, discussed the results and drafted the first manuscript. SQ conducted the parameter estimation and numerical simulations. AY and SZ carried out the numerical simulations and discussed the results. Each author carefully read the revised version and gave final approval for submission of the article.

Declaration of competing interest

None.

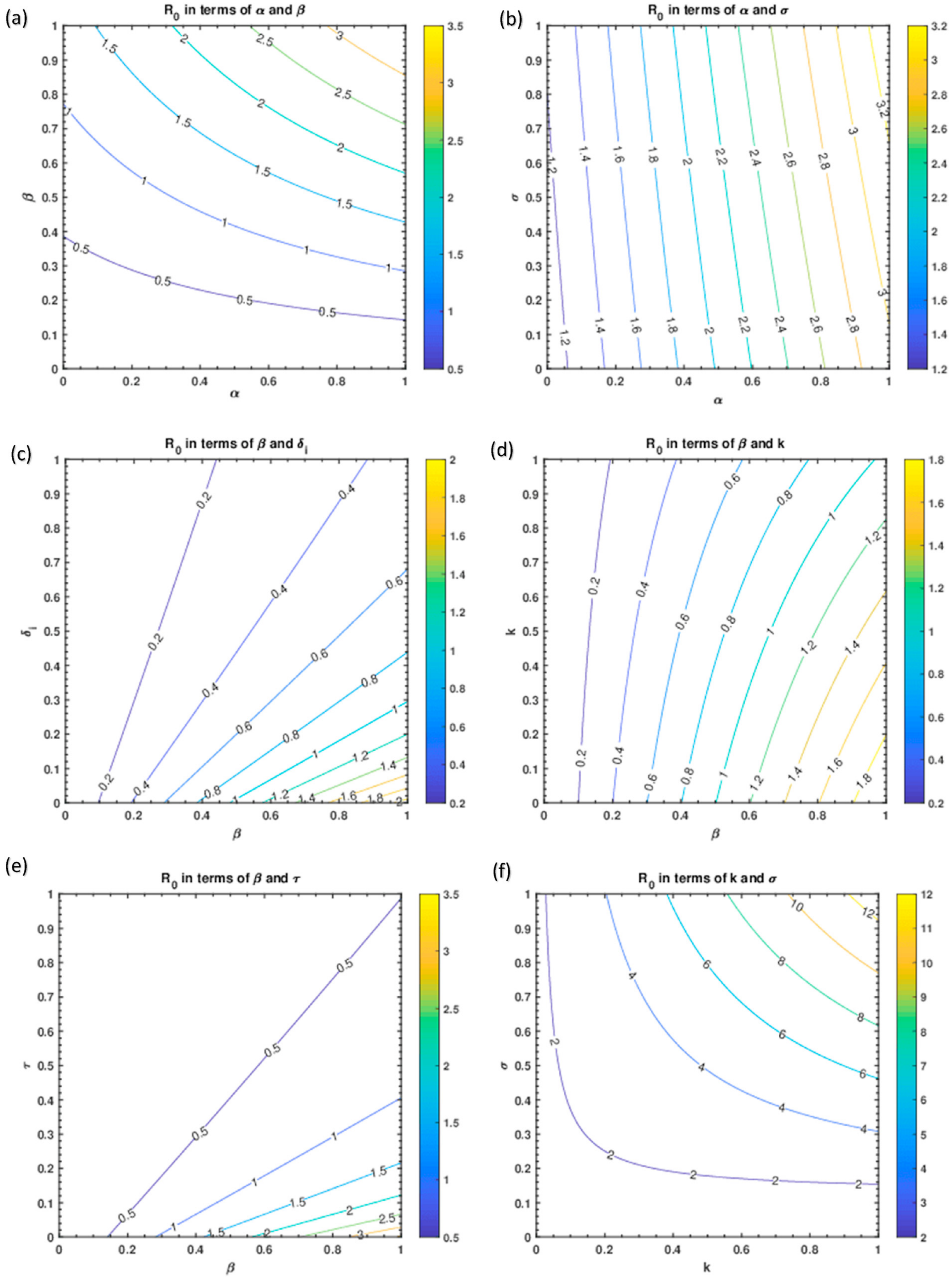

Fig. 6. Contour plots of the basic reproduction number R_0 in terms of the controllable parameters with R_0 as a response function.

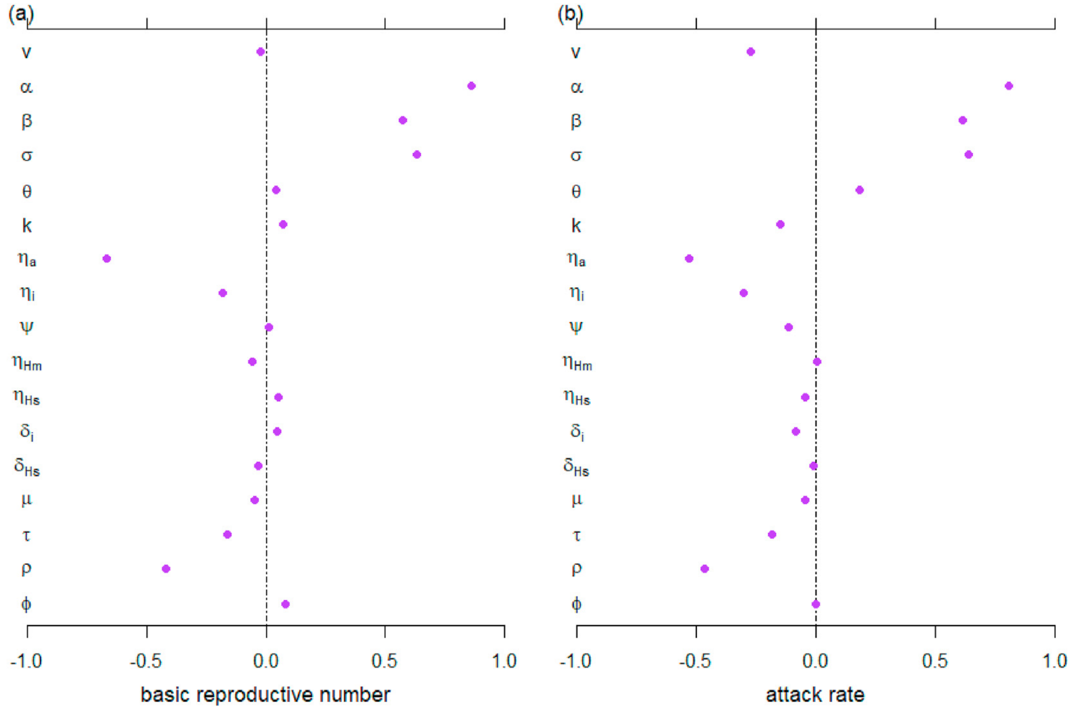

Fig. 7. Plot of the PRCCs of R_0 for the sensitivity analysis against the parameters of the model given in Table 2. The circle dots (in purple) are the estimated correlations and the bars are the 95% CIs.

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