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ORIGINAL ARTICLE

NICOV : a model to analyse impact of nutritional status and immunity on COVID-19

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Abstract
A few months back there was no medication and vaccine for COVID-19. Yet, most of the infected people got recovered. A very small portion of the infected people could not recover. A lion's share of the fatal cases were the patients suffering from some kind of chronic critical diseases. Due to that, their nutritional status and immunity were not normal. In this study, we have proposed a model called NICOV (Nutritional status, Immunity and COVID) that establishes the relationship among nutritional status, immunity, and COVID-19. This model formulates the relations considering all possible states of nutritional status and immunity of the body. We have numerically simulated the model for four different sets of values and found that susceptible, infected, and recovered cases of COVID-19 are significantly related to different states of nutritional status and immunity. It is also evident from numerical simulation that the effect of nutritional status and immunity varies with variation of other parameters associated with the formulation of the model. This model can help the concerned in decision making for mitigation of the losses that arise due to COVID-19-like situations.

Keywords Nutritional status and COVID-19 · Malnutrition and immunity · Immunity and COVID-19 · Fighting COVID-19 with immune system · Corona virus and immunity

1 Introduction

The COVID-19 is a new disease evolved in December 2019. This disease is caused by a virus called SARS-CoV-2 [4]. This virus is termed as nCoV-2 or COVID-19 virus or even simply coronavirus. Coronavirus was there from long back but the latest one has a unique set of DNA structure [14, 18]. This virus mainly affects the respiratory system causing a new kind of pneumonia [5, 10]. The patients infected by COVID-19 virus can be symptomatic or asymptomatic. Symptomatic patients show some symptoms like fever, cough, cold, etc., but asymptomatic patients do not show any symptoms [9]. So, there is a high possibility of spreading this virus by the asymptomatic patients. This disease has a very high rate of infection but a low rate of fatality. This disease is vulnerable to patients suffering from heart problems, high blood pressure, kidney issues, liver issues, respiratory system issues, cancer, diabetes, etc. [2]. If there is no other major problem in the body, most of the patients get cured without any special treatment [23]. Maintaining social distance, frequently washing hands, frequent use of sanitizer, maintaining personal hygiene, wearing mask, not touching face and nose with bare hands, etc. have been suggested as preventive measures. To date, some vaccines have been developed and authorities of most of the countries of the world have given permission for emergency use of those vaccines. As of November 2021, seven vaccines have been approved for emergency or full use by WHO recognized stringent regulatory authority. These are Pfizer-BioNTech, Oxford-AstraZeneca, Sinopharm BIBP, Moderna, Janssen, CoronaVac, and Covaxin. Five other vaccines are under WHO's assessment. Those are Sputnik V, Sinopharm WIBP, Convidecia, Novavax, and Sanofi-GSK. Besides these vaccines, DRDO of India has developed an anti-COVID medicine called 2-DG and that has also been permitted for emergency use only. However, there is ample scope for further development of vaccines and medications.

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Now there is a question. Why is the fatality rate higher in patients that are suffering from some other diseases than that of the patients only infected by coronavirus? In this point, we can bring the relation of malnutrition and immunity of the body. In our earlier studies [7, 8], it has been mentioned that due to suffering from other diseases, there is a high probability of developing malnutrition. Nutritional status and immunity of the body are highly correlated. Though the immune system is the soldier of our body, it needs support in the form of nutrients. An adequate amount of nutrition along with sound state of the body supports the immune system properly and makes it strong enough to fight against the germs [6]. Since there is no confirmed and end stage treatment for this disease in particular, the immunity of the body is the only source of dependence to get cured of infection. The relationship between nutrition and immunity is well known and its role in coronavirus disease 2019 is also getting importance. The under-developing and developing countries like India have a very big figure of malnutrition among people [22]. So, there is a very high risk of fatality due to COVID-19 in India as malnutrition weakens the immune system of the body and thus immune system of the body fails in the fight against COVID-19. It is expected that during this crisis there will be a compromise in nutritional status of the body [13]. Nutritional status has to be considered in the risk profile of coronavirus patients as malnutrition is a powerful risk factor similar to different comorbidities [17].

To see how nutritional status and immunity affect various possibilities of coronavirus disease, we can have mathematical models. The models can be designed considering different cases and these models can perform different tasks. There are some models that work on prediction, some work on analysing the changes with time, and some are for showing relations among different factors [11, 21]. The main objective of this work is to establish the relationship among nutritional status, immunity and COVID-19 like diseases. To achieve this objective, the followings have been incorporated with this work:

- To formulate a mathematical model that integrates nutritional status, immunity of the body, and COVID-19.
- To mathematically simulate the model to see how different parameters react.
- To check how nutritional status and immunity of the body affect susceptibility, infection, and recovery of COVID-19.

To get an idea about the current status, we perform an extensive literature survey on the works related to nutritional status, immunity, and COVID-19. Some of the most related works are mentioned in brief. The work in [16] has presented a framework for action to maintain optimal nutrition at the individual, community, national, and global levels. This work used an adapted version of the ecological model of health behavior to enhance the physical and mental health of individuals in regard to COVID-19 pandemic. From this study, it is clear that diet has a profound effect on people's immune system and disease susceptibility. It also affirms that specific nutrients or nutrient combinations may affect the immune system through the activation of cells, modification in the production of signaling molecules, and gene expression. The study in [1] has mentioned that it is mandatory to attain and maintain good nutritional status to fight against the virus. Nutritional status of individuals has been used as resilience towards destabilization during this COVID-19 pandemic. Optimal nutrition and dietary nutrient intake impact the immune system. Therefore, the only sustainable way to survive in the current context is to strengthen the immune system. This article explores the importance of nutrition to boost immunity and gives some professional and authentic dietary guidelines about nutrition and food safety to withstand COVID-19. The study in [19] mentions that cancer and transplant patients with COVID-19 have a higher risk of developing severe and even fatal respiratory diseases, especially as they may be treated with immune-suppressive or immune-stimulating drugs. This study used Ovid MEDLINE, the largest biomedical information database to review the current evidences of immune-suppressing or stimulating drugs. The study in [20] talks about a mathematical model called Bats-Hosts-Reservoir-People transmission fractional order that uses fractional derivative. They have used iterative Laplace transform method for numerical computations. The authors got motivated by the Caputo-Fabrizio operator and investigated different dynamics of COVID-19 based on human to human transmission and also reservoir to human transmission. They develop the models according to the disease characteristics in terms of Caputo-Fabrizio fractional differential systems of equations. The study in [3] talks about a deterministic compartmental model to study the spreading of COVID-19 and sensitivity analysis has been done to identify the key parameters. Their model divides the populations in a total of seven mutually exclusive compartments based on the disease status. They formulate differential equations for all those seven categories and simulate the model. The study in [15] formulated a mathematical model to capture the dynamics of COVID-19 incorporating the disease characteristics that is based on deterministic ordinary differential equations. This model assumes frequency-dependent disease transmission and homogeneous-mixing approximation. Their model has a unique aspect of modelling the trace-and-isolate protocol. They formulate the conceptual model and corresponding differential equations and simulate and analyse those equations.

From the literature review, it has been found that some studies have been carried out for mathematically modelling malnutrition. Some of the studies are only about modelling the immune system of human body. Correlation between malnutrition and immunity has also been studied a bit. Correlation between malnutrition and COVID-19, and correlation between immunity and COVID-19 have been studied separately. We could find that the correlation among malnutrition, immunity, and COVID-19 all together can be explored. In this portion, very limited works have been carried out. So, our study will be to find correlation among malnutrition, immunity, and COVID-19.

2 Method

2.1 Proposed workflow

The workflow of this proposed work is shown in Fig. 1. We plan to see the relation among nutritional status and immunity of the body with COVID-19. For this, we study so many works that are related to nutritional status and COVID-19, immunity and COVID-19, nutritional status and immunity of the body, nutritional status and its relation with other infectious disease, immunity and its relation with other infectious diseases, etc., and we find that individual studies are available for nutritional status with COVID-19 and immunity with COVID-19. But we find a scope for exploring the relation together with nutritional status, immunity, and COVID-19. So, we take help from some papers and formulate a model called NICOV. This model integrates nutritional status and immunity with COVID-19-like diseases. It calculates susceptibility, infection, and recovery considering nutritional status and immunity. After formulating the model, we numerically simulate the model using four different sets of values. After that, we work on establishing the relation among nutritional status, immunity, and COVID-19 considering all possible states of nutritional status and immunity. We get four different cases and all these four cases have been studied separately.

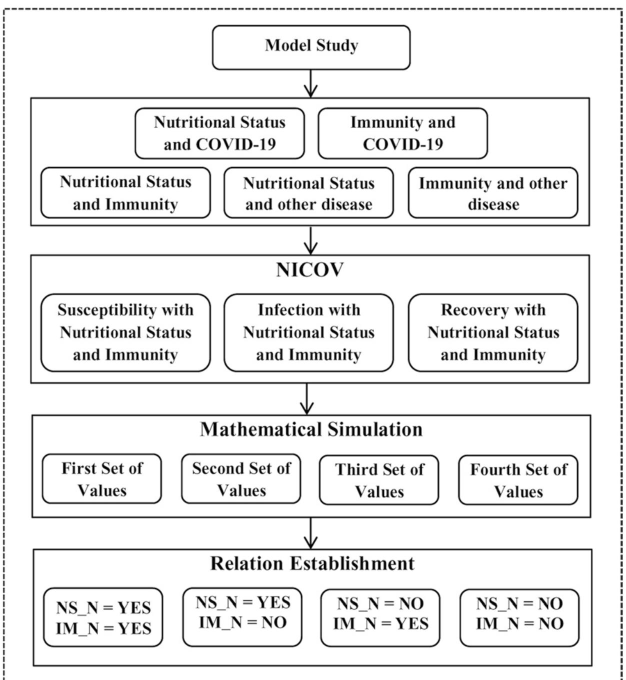
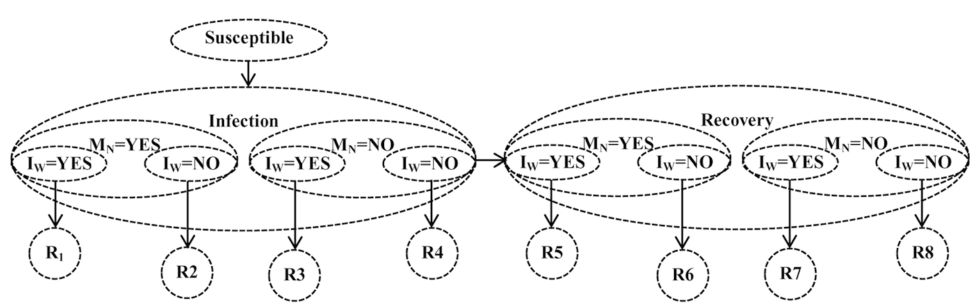


Fig. 1 Proposed workflow

2.2 Preliminary concepts behind the proposed model

For this study, we plan to develop a mathematical model for finding relation among malnutrition, immunity, and COVID-19. We consider all possible levels of malnutrition and immunity. Then, we develop the equations for susceptibility, infection, and recovery for COVID-19. So, basically we consider two states of nutritional status namely malnutrition ($M_N = YES$) and normal nutrition ($M_N = NO$). Similarly, we consider two states of immunity in human body namely weak immunity ($I_W = YES$) and normal immunity ($I_W = NO$). Considering all these cases, we proceed as per Fig. 2. Figure 2 is a tree structure approach that is followed for creating our mathematical model. In the last leaf, we suppose the possible results as $R_1, R_2, \cdot, R_8$. These results are based on different situations considered for model formulation.

Fig. 2 Flow adopted in the formulation of mathematical model



2.3 NICOV: the model and its formulation

To formulate the mathematical model to study the relationship among nutritional status, immunity, and COVID-19, we make some assumptions. In making these assumptions, we refer to the studies in [12, 15] and [20]. The assumptions that we make are as follows:

- The COVID-19 model classifies the human population at time t, denoted by $N(t)$, into:
  (a) Susceptible individuals $[S_{ij}(t)]$.
  (b) COVID-19-infected individuals $[I_{ij}(t)]$, and
  (c) Recovered individuals $[R_{ij}(t)]$.
  Where, $i = (1, 2)$ with $i = 1$ denoting nourished individuals, and
  $i = 2$ denoting malnourished individuals,
  $j = (1, 2)$ with$j = 1$ denoting individual with strong immunity,
  $j = 2$ denoting individual with weak immunity.
- The pathogen population at time t is $P(t)$.
- It is assumed that susceptible humans are recruited into the population at a constant rate Λ.
- A portion of the susceptible individuals K_{11} are assumed to be nourished and having strong immunity. A portion of the susceptible individuals K_{12} are assumed to be nourished and having weak immunity. A portion of the susceptible individuals K_{21} are assumed to be malnourished and having strong immunity. A portion of the susceptible individuals $K_{22}[1 - K_{11} - K_{12} - K_{21}]$ are assumed to be malnourished and having weak immunity.
- Nourished susceptible may move to malnourished susceptible class at a constant rate r_n due to food shortage and other reasons.
- Strong immunity susceptible may move to weak immunity susceptible class at a constant rate r_i due to malnutrition and other reasons.
- Let the susceptible S_{11}, S_{12}, S_{21}, and S_{22} acquire COVID-19 infection following contact with pathogen at the rate $\lambda, \alpha\lambda, \beta\lambda$, and $\gamma\lambda$, respectively, where, $\alpha > 1, \beta > 1, \gamma > 1$, and $\alpha < \beta < \gamma$.
- The infection rate λ is given by: $\lambda = \frac{eP}{C+P}$, where, e is the exposure to pathogen per unit time and C is the concentration of nCoV-2 in the medium.
- $\lambda(P) = \frac{P}{C+P}$ is the probability that an individual in contact with the pathogen is infected
- S_{11}, S_{12}, S_{21}, and S_{22} move to I_{11}, I_{12}, I_{21}, and I_{22} at the rates $\lambda, \alpha\lambda, \beta\lambda$, and $\gamma\lambda$, respectively, where $\alpha > 1, \beta > 1, \gamma > 1$, and $\alpha < \beta < \gamma$.
- I_{11}, I_{12}, I_{21}, and I_{22} recover at the rate r_{11}, r_{12}, r_{21}, and r_{22}
- I_{11}, I_{12}, I_{21}, and I_{22} die at the rate $\eta, a\eta, b\eta$, and $c\eta$, respectively, where $a > 1, b > 1, c > 1$, and $a < b < c$.
- Natural death rate ⋏ |.
- The pathogen population is generated at a rate g.
- Pathogens growth in I_{11}, I_{12}, I_{21} and I_{22} at a constant rate σ which is a measure of the contribution of each infected individual to the population of nCoV-2 in the medium.
- The SARS-CoV-2 has a natural death rate μ_0.

Putting the assumption and their intermediate formulations together gives the following differential equations:

$$
\begin{aligned}
S'_{11}(t) &= K_{11}\Lambda - \frac{eP}{C+P}S_{11} - (\mu + r_n + r_i)S_{11} \\
S'_{12}(t) &= K_{12}\Lambda + r_i S_{11} - \alpha\frac{eP}{C+P}S_{12} - (\mu + r_n)S_{12} \\
S'_{21}(t) &= K_{21}\Lambda + r_n S_{11} - \beta\frac{eP}{C+P}S_{21} - (\mu + r_i)S_{21} \\
S'_{22}(t) &= K_{22}\Lambda + (r_n + r_i)S_{11} - \gamma\frac{eP}{C+P}S_{22} - \mu S_{22} \\
I'_{11}(t) &= \frac{eP}{C+P}S_{11} - (r_{11} + \mu + \eta)I_{11} \\
I'_{12}(t) &= \alpha\frac{eP}{C+P}S_{12} - (r_{12} + \mu + a\eta)I_{12} \\
I'_{21}(t) &= \beta\frac{eP}{C+P}S_{21} - (r_{21} + \mu + b\eta)I_{21} \\
I'_{22}(t) &= \gamma\frac{eP}{C+P}S_{22} - (r_{22} + \mu + c\eta)I_{22} \\
R'_{11}(t) &= r_{11}I_{11} - \mu R_{11} \\
R'_{12}(t) &= r_{12}I_{12} - \mu R_{12} \\
R'_{21}(t) &= r_{21}I_{21} - \mu R_{21} \\
R'_{22}(t) &= r_{22}I_{22} - \mu R_{22} \\
P'(t) &= gP + \sigma(I_{11} + I_{12} + I_{21} + I_{22}) - \mu_0 P
\end{aligned}
\tag{1}
$$

These differential equations are for susceptible, infected, and recovered cases. These equations can be mathematically simulated considering some initial values and we can see how do susceptible, infected and recovered cases change with time.

2.3.1 Algorithm of NICOV

The algorithm for the formulated model can be as follows. The details about the parameter space used in the algorithm are the same as shown in Section 2.3.

2.4 Experimentation

To simulate this model, we carry out the experiments on a system with 3GB RAM, 3MB cache memory, and 2.10GHz of clock speed. We work on Ubuntu 18.04 LTS operating system. We use Python3.6 in Jupyter notebook. The

Algorithm 1 Steps involved in the NICOV model.

Result: Change in S, I, and R
Define M_N, I_W
Step 1: Check for M_N to be YES or NO [Set flag for Malnutrition 1 or 0]
Step 2: Check for I_W to be YES or NO [Set flag for Malnutrition 1 or 0]
Step 3: Calculate
if $M_N == YES$ **then**
  if $I_W == YES$ **then**
    $S'_{22}(t) = K_{22}\Lambda + (r_n + r_i)S_{11} - \gamma\frac{eP}{C+P}S_{22} - \mu S_{22}$
    $I'_{22}(t) = \gamma\frac{eP}{C+P}S_{22} - (r_{22} + \mu + c\eta)I_{22}$
    $R'_{22}(t) = r_{22}I_{22} - \mu R_{22}$
  else
    $S'_{21}(t) = K_{21}\Lambda + r_n S_{11} - \beta\frac{eP}{C+P}S_{21} - (\mu + r_i)S_{21}$
    $I'_{21}(t) = \beta\frac{eP}{C+P}S_{21} - (r_{21} + \mu + b\eta)I_{21}$
    $R'_{21}(t) = r_{21}I_{21} - \mu R_{21}$
  end
else
  if $I_W == YES$ **then**
    $S'_{12}(t) = K_{12}\Lambda + r_i S_{11} - \alpha\frac{eP}{C+P}S_{12} - (\mu + r_n)S_{12}$
    $I'_{12}(t) = \alpha\frac{eP}{C+P}S_{12} - (r_{12} + \mu + a\eta)I_{12}$
    $R'_{12}(t) = r_{12}I_{12} - \mu R_{12}$
  else
    $S'_{11}(t) = K_{11}\Lambda - \frac{eP}{C+P}S_{11} - (\mu + r_n + r_i)S_{11}$
    $I'_{11}(t) = \frac{eP}{C+P}S_{11} - (r_{11} + \mu + \eta)I_{11}$
    $R'_{11}(t) = r_{11}I_{11} - \mu R_{11}$
  end
end
Step 4: Stop

Where, S_{ij}, I_{ij}, R_{ij} represents Susceptibility, Infection and Recovery respectively under i nutritional status and j immunity. A value of 1 means normal, while 2 means abnormal.

computational complexity for running this algorithm can be estimated by analysing the individual steps involved in the algorithm. Since this model has differential equations, we intend to see the changes in terms of time. Each individual differential equation will be solved using finite sets of values for the parameters. So, for a particular case, the space complexity will not have much significance. This is because the values are within a predefined limit. But, for different initial values of differential equations within that limit, the equations will converge at a different time period. This convergence will also be affected by the type of system used as the system may have higher or lower configuration and different computational capability. Hence, computational time will vary based on the initial values and also the type of system used.

3 Results

The formulated model has been numerically simulated considering the values mentioned in Table 1. We consider four sets of parameter values in total. As our objective of the work is to find relationship among nutritional status, immunity, and COVID-19, in the model we consider all possible states of nutritional status and immunity. The simulation of the model will show how different conditions of nutritional status and immunity effect the change in susceptible, infected, and recovered cases in COVID-19. From the simulation itself, we will understand the sensitivity of different parameters of the model.

Table 1 Parameter values used in the simulations

Parameter	Symbol	Value-1	Value-2	Value-3	Value-4
Portion of nourished and strong immunity	K_{11}	60%	51%	42%	33%
Portion of nourished and weak immunity	K_{12}	15%	18%	21%	24%
Portion of malnourished and strong immunity	K_{21}	15%	18%	21%	24%
Portion of malnourished and weak immunity	K_{22}	10%	13%	16%	19%
Recruitment rate	Λ	$10day^{-1}$	$20day^{-1}$	$30day^{-1}$	$40day^{-1}$
Pathogen population	P	4	8	12	16
Rate of exposure to contaminated medium	e	5%	10%	15%	20%
Concentration of pathogen	C	1	2	3	4
Natural death rate of susceptible	μ	2%	4%	6%	8%
Rate of becoming malnourished from nourished	r_n	0.010 day^{-1}	0.015 day^{-1}	0.020 day^{-1}	0.025 day^{-1}
Rate of becoming weak immune from strong immune	r_i	0.005 day^{-1}	0.010 day^{-1}	0.015 day^{-1}	0.020 day^{-1}
Growth rate	g	1.98	2.33	3.50	4.50
Natural death rate of pathogen	μ_0	5%	10%	15%	20%
Contribution of infected individual to the population of pathogen	σ	1	2	3	4
Recovery rate for I_{11}	r_{11}	50%	44%	38%	32%
Recovery rate for I_{12}	r_{12}	20%	22%	24%	26%
Recovery rate for I_{21}	r_{21}	20%	22%	24%	26%
Recovery rate for I_{22}	r_{22}	10%	12%	14%	16%
Disease-induced death rate for I_{11}	η	0.03	0.06	0.09	0.12
Disease-induced death rate for I_{12}	$(a = 1.5)\eta$	0.45	0.90	0.135	0.18
Disease-induced death rate for I_{21}	$(b = 2.5)\eta$	0.075	0.15	0.225	0.3
Disease-induced death rate for I_{22}	$(c = 3.5)\eta$	0.105	0.21	0.315	0.42
Infection rate for S_{11}	$\lambda(=\frac{(e\times P)}{(C+P)})$	0.04	0.08	0.12	0.16
Infection rate for S_{12}	$(\alpha = 1.5)\lambda$	0.06	0.12	0.18	0.24
Infection rate for S_{21}	$(\beta = 2.5)\lambda$	0.1	0.2	0.3	0.4
Infection rate for S_{22}	$(\gamma = 3.5)\lambda$	0.14	0.28	0.42	0.56

We divide the population in four possible categories under nutritional status and immunity keeping a standard match with global figures. Globally, almost 20% children are malnourished. This study is not only for children but also covers all categories of population. Also, we use immunity of people. So, we mix nourishment status and immunity and start with 10% of population in the malnourished and weak immune category and gradually increase the percentage to 13%, 16%, and 19% to check the variation in susceptibility, infection, and recovery cases. We keep an equal percentage for mediocre categories of nourishment and immunity. For both "normal nutritional status and weak immunity" and "malnutrition and normal immunity" categories, we start with 15% and then increase to 18%, 21%, and 24%. Similarly for normal nutritional status and normal immunity, we start with 60% and then gradually it has to decrease to 51%, 42%, and 33% with increase in other categories within the percentage limit of 100. These varieties of values help us clearly understand the impact of nutritional status and immunity in different categories of population.

3.1 Results under value-1

In the first set of values, we consider 60% of the population with normal nutritional status and normal immune system, 15% of the population with normal nutritional status and weak immunity, 15% of the population with malnutrition and normal immunity, and 10% of population with malnutrition and weak immunity are there in the susceptibility. Figure 3 shows the change in susceptible cases considering all the parameter values under value-1. Figure 4 shows the change in infected cases considering parameter values under the set value-1. Likewise, Fig. 5 shows the change in recovered cases considering parameter values under the set value-1.

3.2 Results under value-2

In the second set of values, we consider 51% of the population with normal nutritional status and normal immune system, 18% of the population with normal nutritional status and weak immunity, 18% of the population with

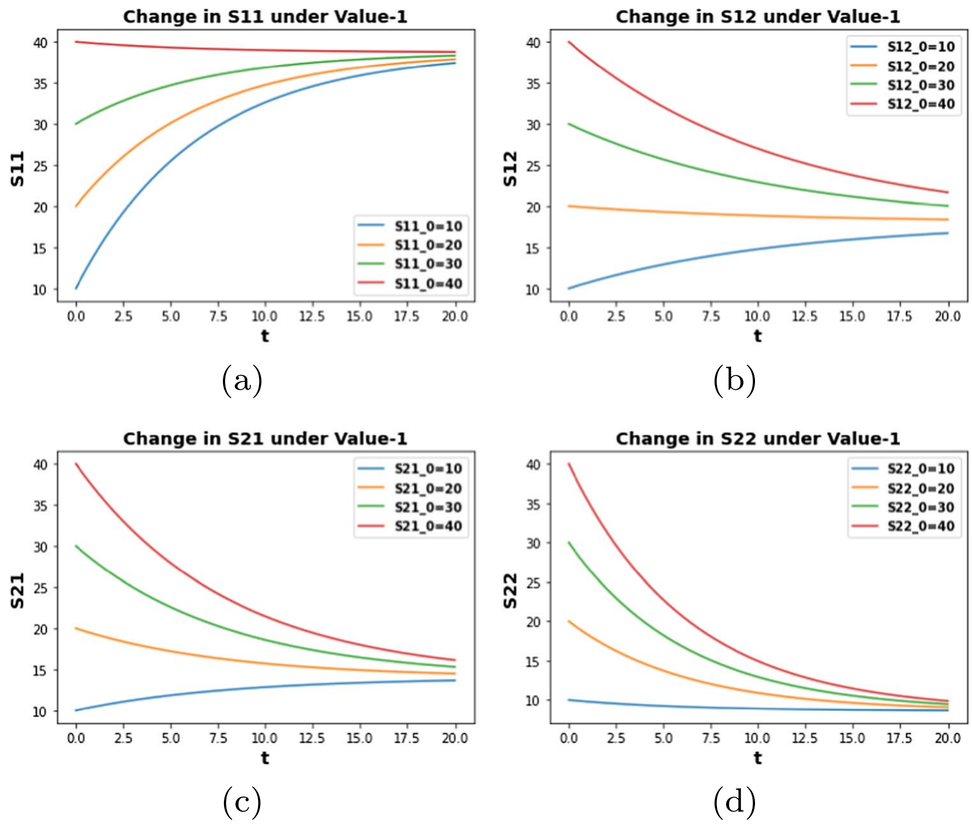


Fig. 3 Change in susceptible cases under value-1: **a** nourished and strong immunity (S_{11}); **b** nourished and weak immunity (S_{12}); **c** malnourished and strong immunity (S_{21}); **d** malnourished and weak immunity (S_{22})

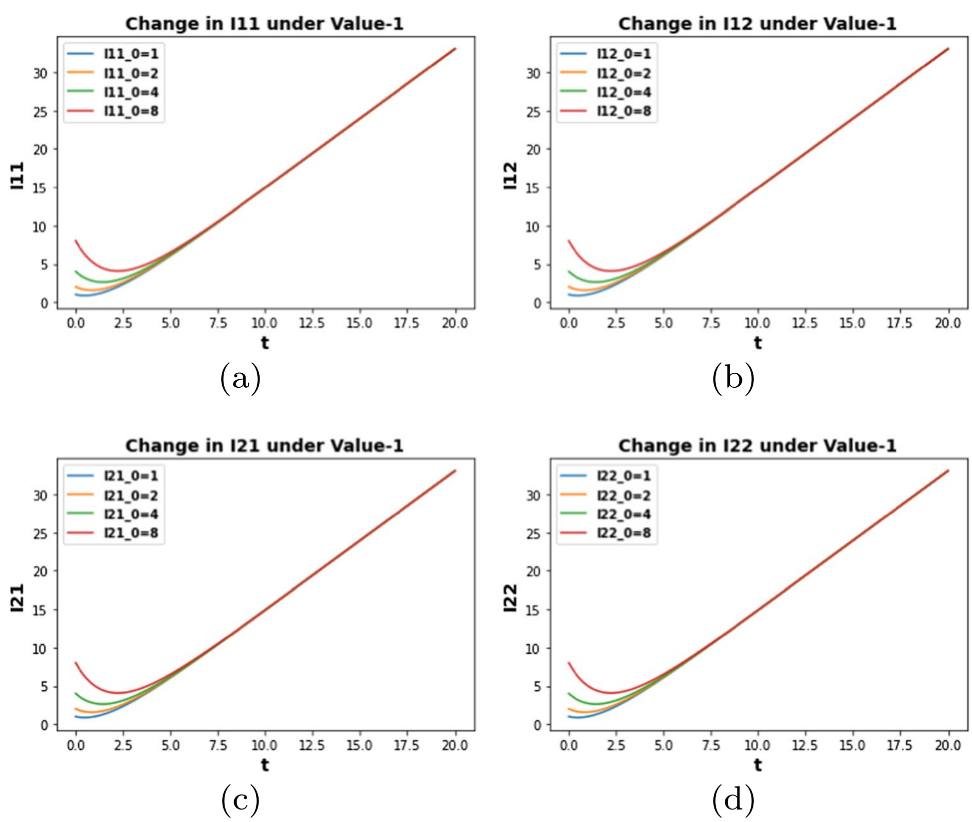


Fig. 4 Change in infected cases under value-1: **a** nourished and strong immunity (I_{11}); **b** nourished and weak immunity (I_{12}); **c** malnourished and strong immunity (I_{21}); **d** malnourished and weak immunity (I_{22})

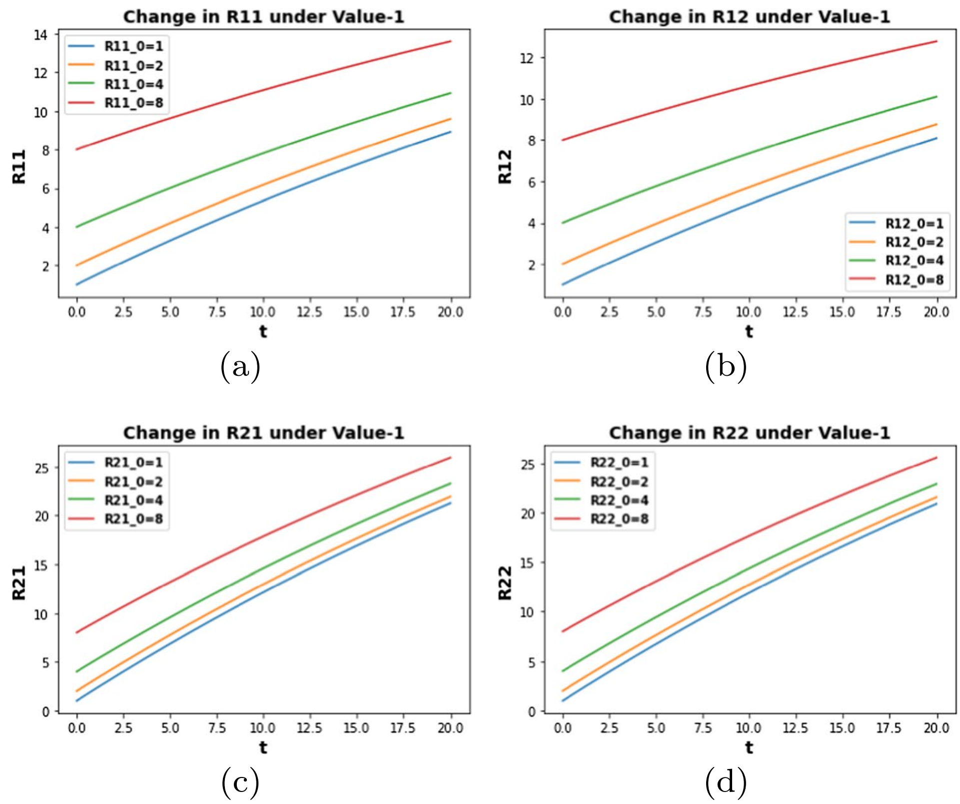


Fig. 5 Change in recovered cases under value-1: **a** nourished and strong immunity (R_{11}); **b** nourished and weak immunity (R_{12}); **c** malnourished and strong immunity (R_{21}); **d** malnourished and weak immunity (R_{22})

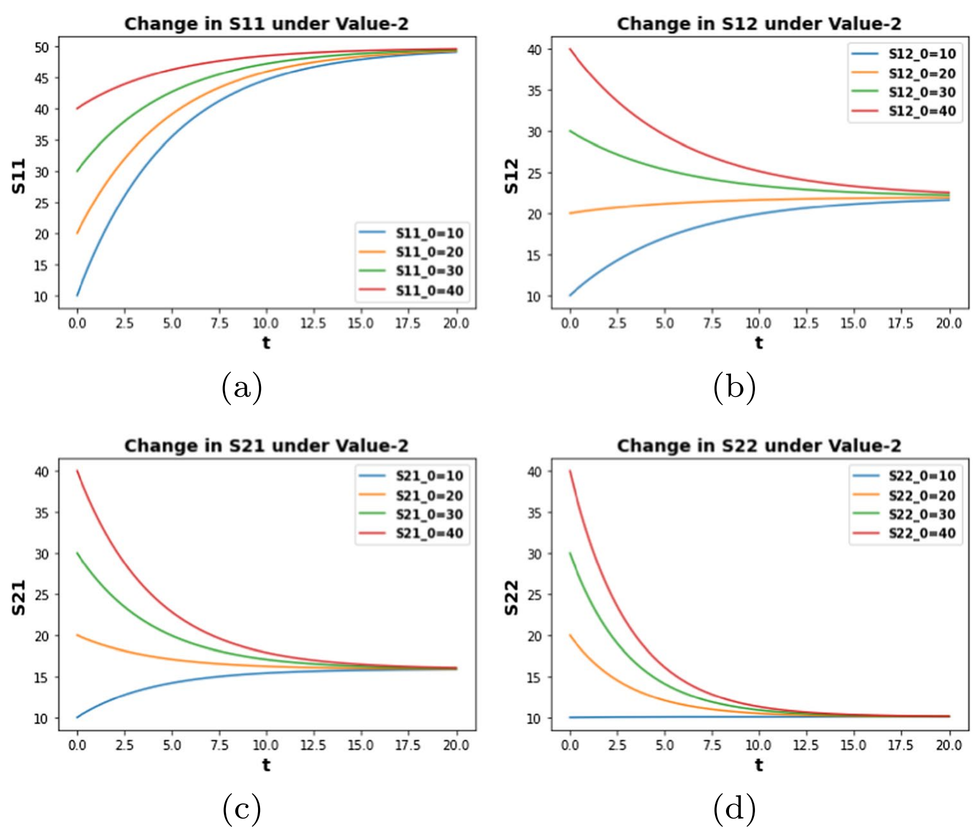


Fig. 6 Change in susceptible cases under value-2: **a** nourished and strong immunity (S_{11}); **b** nourished and weak immunity (S_{12}); **c** malnourished and strong immunity (S_{21}); **d** malnourished and weak immunity (S_{22})

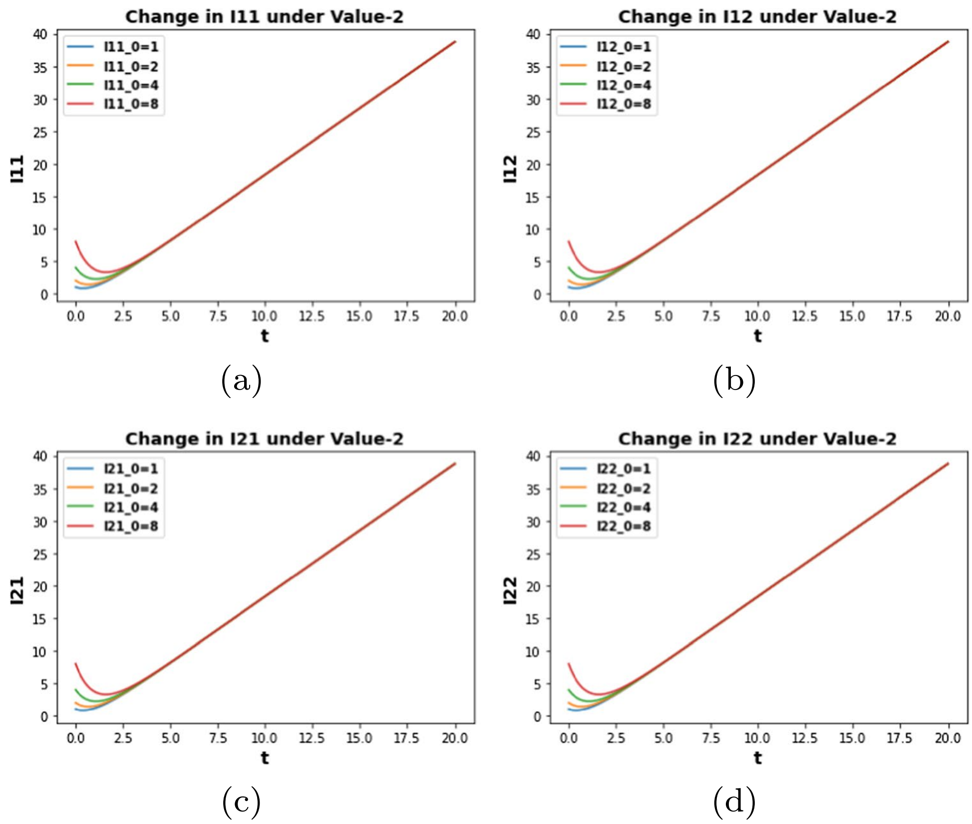


Fig. 7 Change in infected cases under value-2: **a** nourished and strong immunity (I_{11}); **b** nourished and weak immunity (I_{12}); **c** malnourished and strong immunity (I_{21}); **d** malnourished and weak immunity (I_{22})

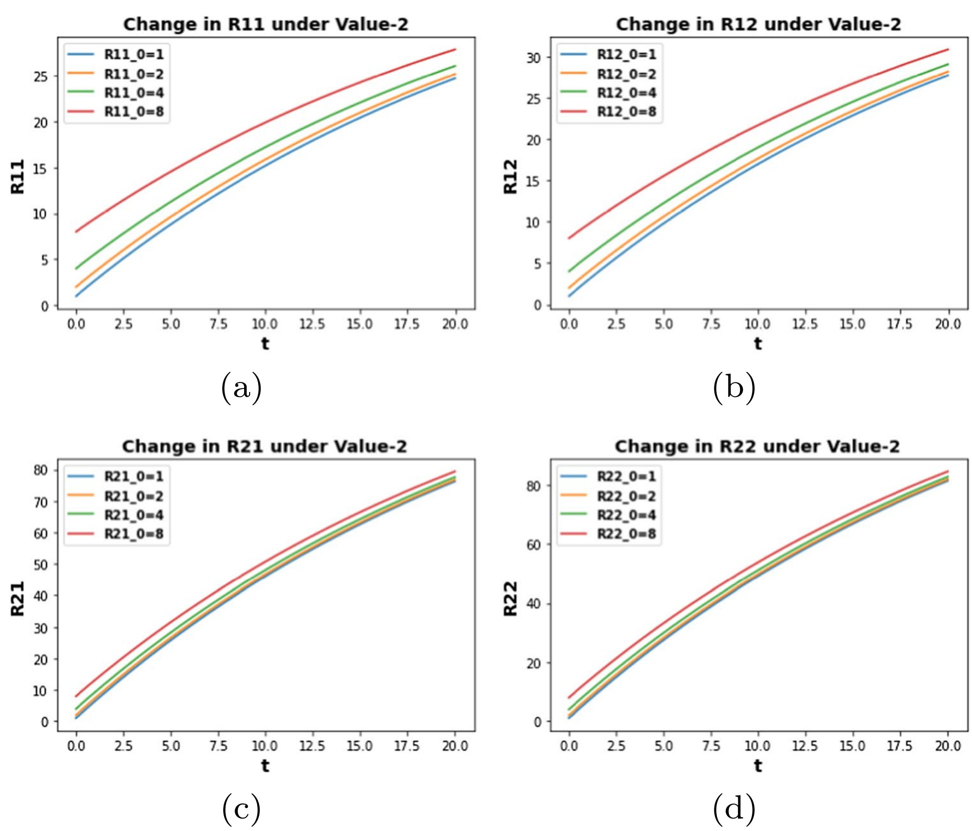


Fig. 8 Change in recovered cases under value-2: **a** Nourished and strong immunity (R_{11}); **b** nourished and weak immunity (R_{12}); **c** malnourished and strong immunity (R_{21}); **d** malnourished and weak immunity (R_{22})

Fig. 9 Change in susceptible cases under value-3: **a** nourished and strong immunity (S_{11}); **b** nourished and weak immunity (S_{12}); **c** malnourished and strong immunity (S_{21}); **d** malnourished and weak immunity (S_{22})

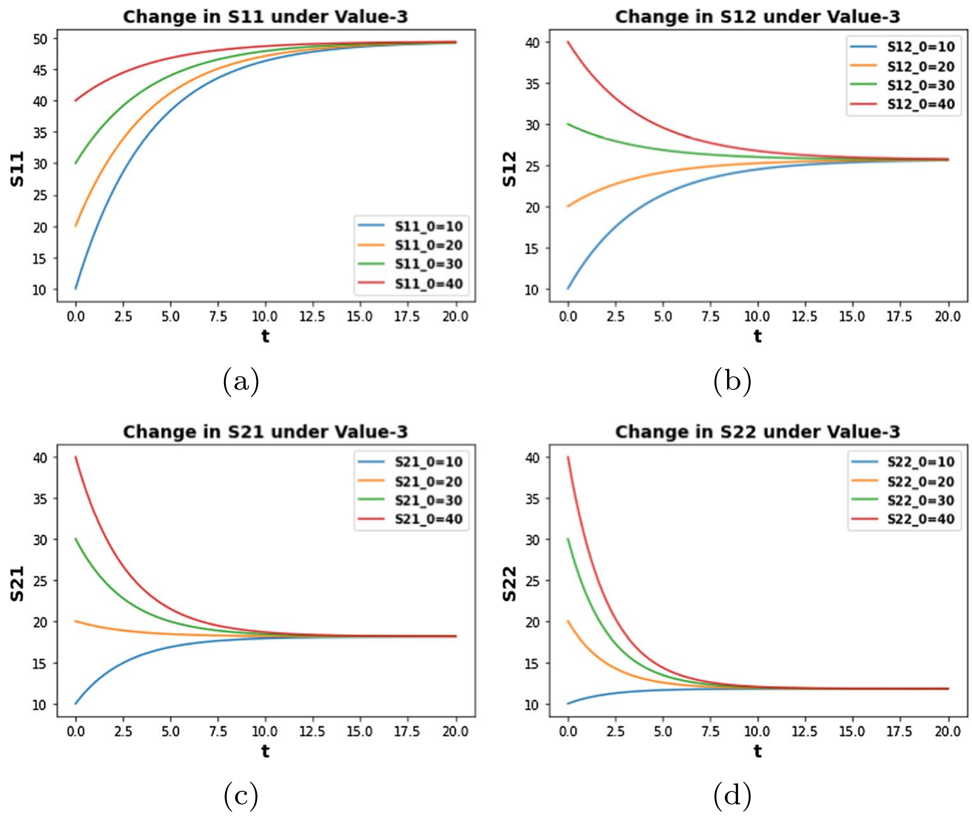
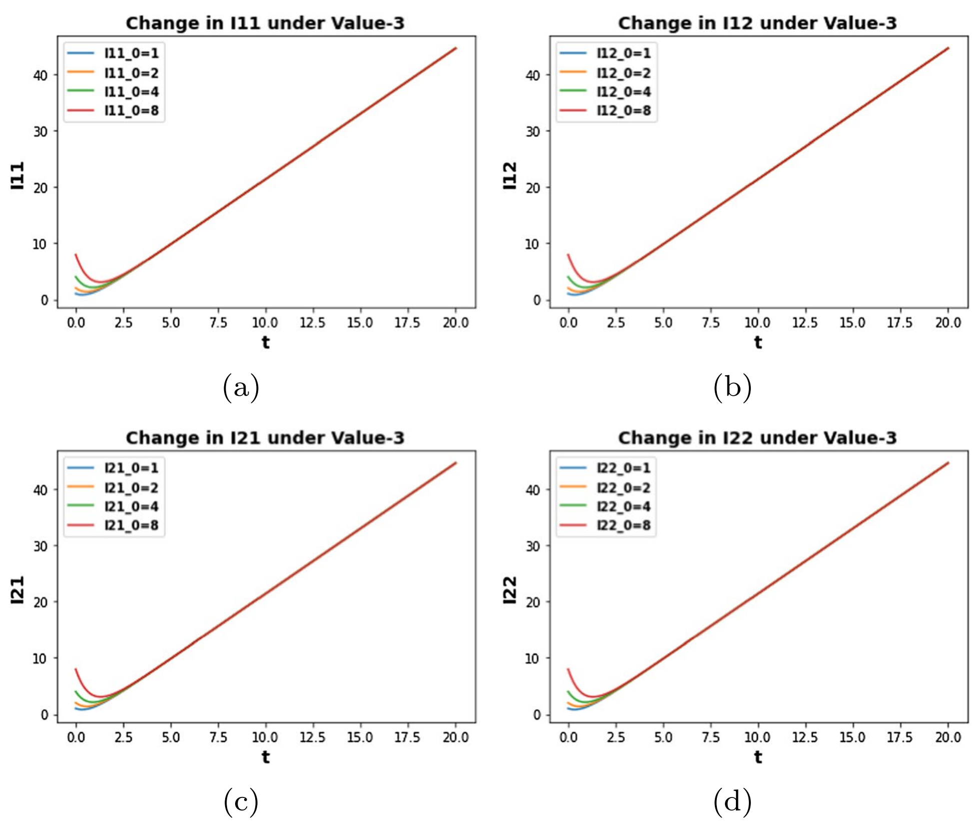


Fig. 10 Change in infected cases under value-3: **a** nourished and strong immunity (I_{11}); **b** nourished and weak immunity (I_{12}); **c** malnourished and strong immunity (I_{21}); **d** malnourished and weak immunity (I_{22})



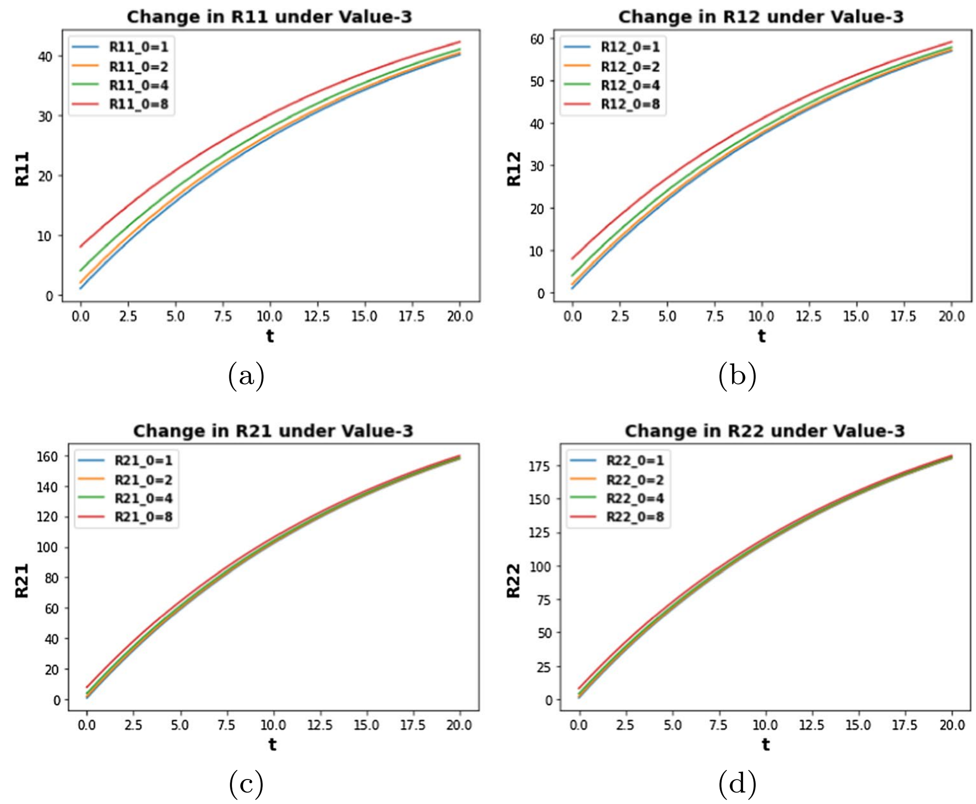


Fig. 11 Change in recovered cases under value-3: **a** nourished and strong immunity (R_{11}); **b** nourished and weak immunity (R_{12}); **c** malnourished and strong immunity (R_{21}); **d** malnourished and weak immunity (R_{22})

malnutrition and normal immunity, and 13% of population with malnutrition and weak immunity are there in the susceptibility. Figure 6 shows the change in susceptible cases considering all the parameter values under value-2. Figure 7 shows the change in infected cases considering parameter values under the set value-2. Likewise, Fig. 8 shows the change in recovered cases considering parameter values under the set value-2.

3.3 Results under value-3

In the third set of values, we consider 42% of the population with normal nutritional status and normal immune system, 21% of the population with normal nutritional status and weak immunity, 21% of the population with malnutrition and normal immunity, and 16% of population with malnutrition and weak immunity are there in the susceptibility. Figure 9 shows the change in susceptible cases considering all the parameter values under value-3. Figure 10 shows the change in infected cases considering parameter values under the set value-3. Likewise, Fig. 11 shows the change in recovered cases considering parameter values under the set value-3.

3.4 Results under value-4

In the fourth set of values, we consider 33% of the population with normal nutritional status and normal immune system, 24% of the population with normal nutritional status and weak immunity, 24% of the population with malnutrition and normal immunity, and 19% of population with malnutrition and weak immunity are there in the susceptibility. Figure 12 shows the change in susceptible cases considering all the parameter values under value-4. Figure 13 shows the change in infected cases considering parameter values under the set value-4. Likewise, Fig. 14 shows the change in recovered cases considering parameter values under the set value-4.

4 Discussions

To solve the differential equations, there is a need of initial value. Based on that initial value, it calculates the changes in values with respect to time. For all three cases, we use four different initial values to check the changes. We intended to start from a small initial value and then gradually increased to see how initial values impact the changes. For susceptibility, we often deploy a bunch of population at a time and hence we use 10, 20, 30, and 40 as the initial values for all four situations. In case of infection, it generally starts with a very small number of population and hence we initialize it by 1, 2, 4, and 8 for all four situations. Likewise, recovery of the infected population is very slow and we initialize it with

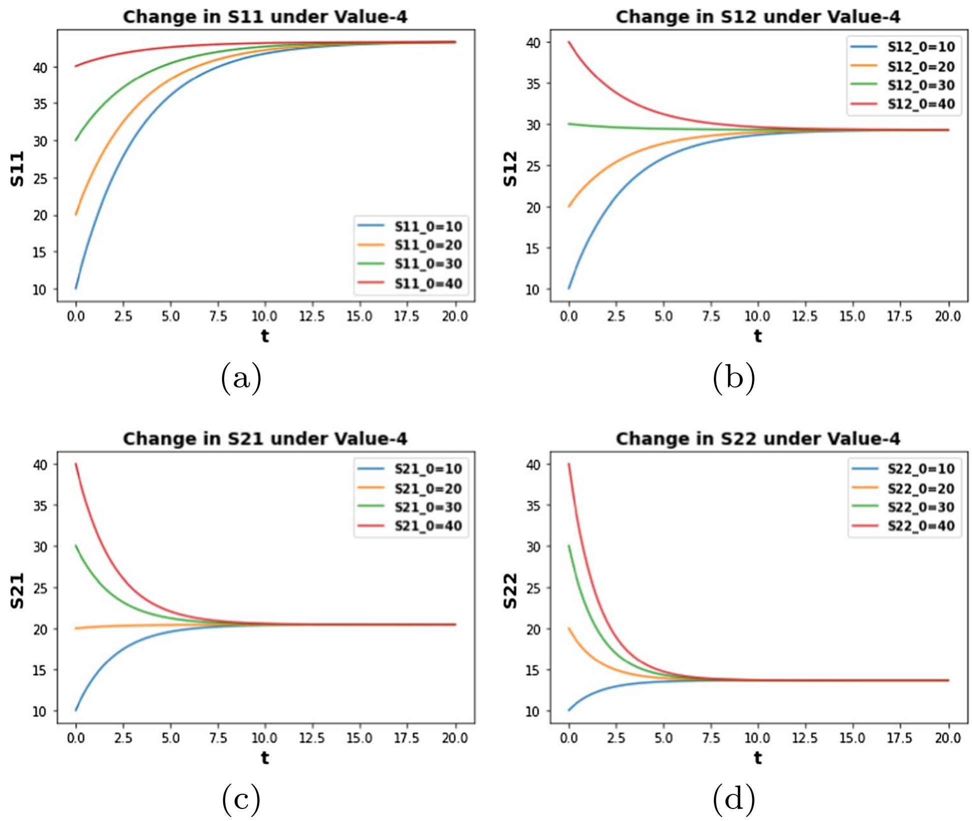


Fig. 12 Change in susceptible cases under value-4: **a** nourished and strong immunity (S_{11}); **b** nourished and weak immunity (S_{12}); **c** malnourished and strong immunity (S_{21}); **d** malnourished and weak immunity (S_{22})

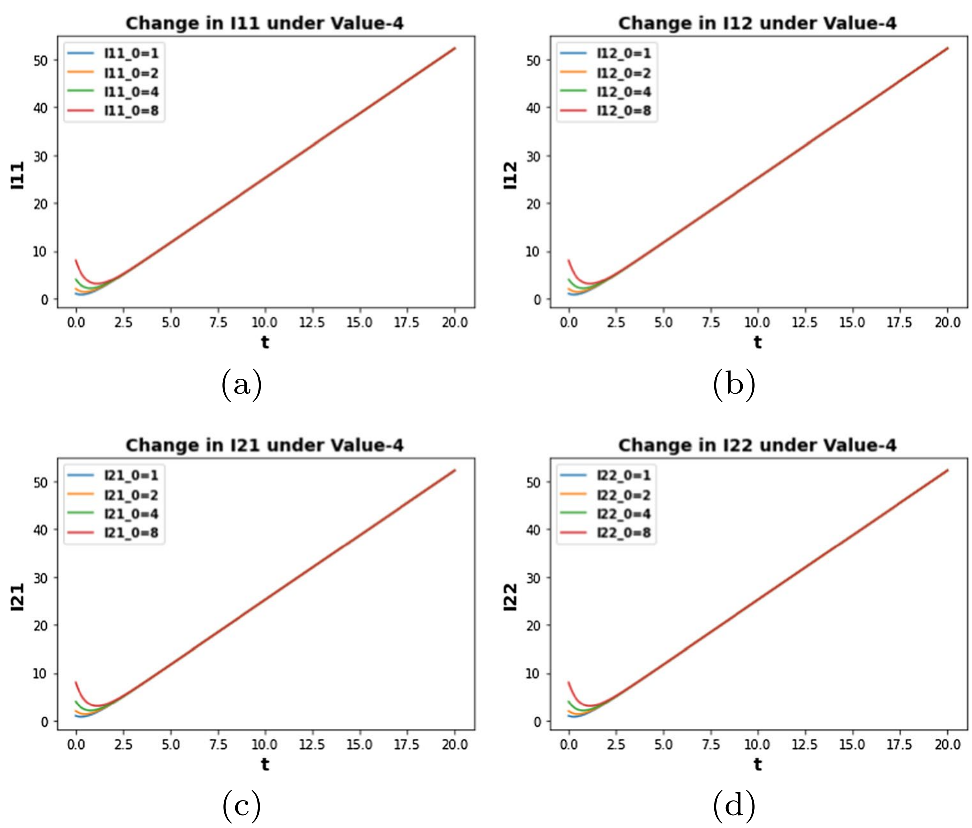


Fig. 13 Change in infected cases under value-4: **a** nourished and strong immunity (I_{11}); **b** nourished and weak immunity (I_{12}); **c** malnourished and strong immunity (I_{21}); **d** malnourished and weak immunity (I_{22})

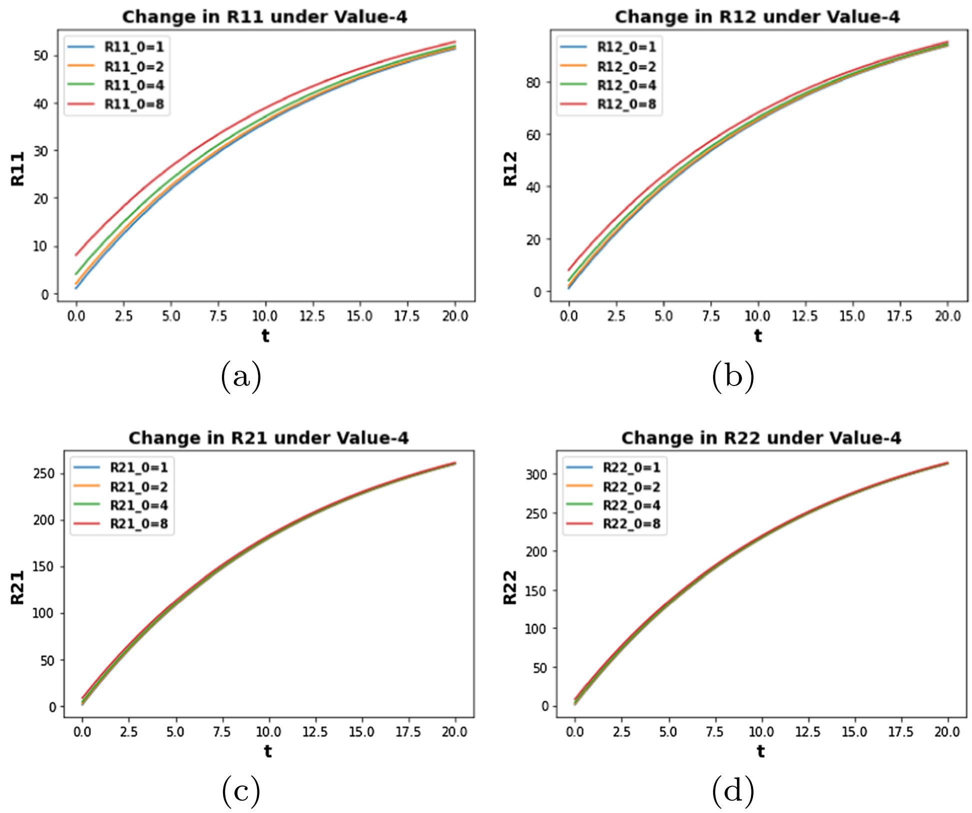


Fig. 14 Change in recovered cases under value-4: **a** nourished and strong immunity (R_{11}); **b** nourished and weak immunity (R_{12}); **c** malnourished and strong immunity (R_{21}); **d** malnourished and weak immunity (R_{22})

values 1, 2, 4, and 8 for all the four situations. These values are clearly depicted in the legends of the corresponding figures. Now, let us see how nutritional status and immunity effect the change in susceptibility, infection, and recovery.

4.1 Establishment of the effect of nutritional status and immunity

From the numerical simulation of the model for all four sets of values, we find that nutritional status and immunity of the body significantly affect the susceptible, infected, and recovered cases of COVID-19. From the plots of differential equations for susceptibility, infection, and recovery, it is evident that different nutritional status and different immunity levels have different types of effects. Now, let us see the effects one by one.

4.1.1 Nutritional status = NORMAL and Immunity = NORMAL

In the case of normal nutritional status and normal immunity, susceptibility, infection, and recovery are denoted by S_{11}, I_{11}, and R_{11}, respectively. Figures 3a, 6a, 9a, and 12a show the changes in susceptible cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values respectively under different initial values. For the first set of values, we find that, for an initial value of 40, it is showing a linear decay, while for the values 10, 20, and 30 it is showing logarithmic growth. For second, third, and fourth sets of values, it is showing logarithmic growth for all initial values. Figures 4a, 7a, 10a, and 13a show changes in infected cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values for different initial values. There is no significant difference in the plots. Figures 5a, 8a, 11a, and 14a show the change in recovered cases for normal nutritional status and normal immunity under the first set of values for different initial values. Here also, no significant change is visible in the plots.

4.1.2 Nutritional status = NORMAL and Immunity = WEAK

In the case of normal nutritional status and weak immunity, susceptibility, infection, and recovery are denoted by S_{12}, I_{12}, and R_{12} respectively. Figures 3b, 6b, 9b, and 12b show the changes in susceptible cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values respectively under different initial values. For the first and second sets of values, we find that, for an initial value of 10, it is showing logarithmic growth. For 20, it is showing almost linear and steady while for 30 and 40, it is showing logarithmic decay. For the third set of values, a logarithmic growth is seen for initial values 10 and 20, while logarithmic decay is seen for 30 and 40. For the fourth set of values, a logarithmic growth is seen for initial values 10 and 20, linear and steady for initial value 30, but for 40, it is a logarithmic decay. Figures 4b, 7b, 10b, and 13b show the changes in infected cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values for different initial values. No significant difference is seen in the plots. Figures 5b, 8b, 11b, and 14b show the changes in recovered cases for normal nutritional status and normal immunity under the first set of values with different initial values. All plots are almost of similar kind.

4.1.3 Nutritional status = MALNUTRITION and Immunity = NORMAL

In the case of malnutrition and normal immunity, susceptibility, infection, and recovery are denoted by S_{21}, I_{21}, and R_{21} respectively. Figures 3c, 6c, 9c, and 12c show the changes in susceptible cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values respectively for different initial values. In all the four sets of values, we observe that, for an initial value of 10, it is showing logarithmic growth. For the initial values 20, 30, and 40, it is showing logarithmic decay except for the fourth set of value. It is seen to be linear and steady. Figures 4c, 7c, 10c, and 13c show changes in infected cases for normal nutritional status and normal immunity under the first, second, third, and fourth sets of values. Under all the initial values, the plots are almost of similar kind. Figures 5c, 8c, 11c, and 14c show the changes in recovered cases for normal nutritional status and normal immunity under the first set of values. Here also, for all the initial values, the plots have not shown significant difference.

4.1.4 Nutritional status = MALNUTRITION and Immunity = WEAK

In the case of malnutrition and weak immunity, susceptibility, infection, and recovery are denoted by S_{22}, I_{22}, and R_{22} respectively. Figures 3d, 6d, 9d, and 12d show the changes in susceptible cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values respectively. For all four sets, we find that, under an initial value of 10, it is almost linear and steady. But, for the initial values 20, 30, and 40, it is showing an exponential decay except for the first set of values, which is a logarithmic decay. Figures 4d, 7d, 10d, and 13d show changes in infected cases for normal nutritional status and normal immunity under first, second, third, and fourth sets of values. Under all initial values, it is not showing significant difference in plots. Figures 5d, 8d, 11d, and 14d show the changes in recovered cases for normal nutritional status and normal immunity under the first set of values. Here, all plots are almost of similar kind.

From the plots, it is evident that there is a great impact of nutritional status and immunity on COVID-19. The effect is clearly visible in the case of susceptibility, though infection and recovery have not shown that much volatility. However, after a certain point of time, it gets converged. For value-1, S_{11} tries to converge around 35 at $t > 20$, $S_{12} \approx 20$ at $t > 20$, $S_{21} \approx 15$ at $t > 20$, $S_{22} \approx 10$ at $t > 20$. I_{11}, I_{12}, I_{21}, I_{22} converge at $t \approx 5$ and linearly moves upward. The R_{11}, R_{12}, R_{21}, R_{22} react differently for different initial values and showing that these will converge at $t > 20$.

For value-2, $S_{11} \approx 45$ at $t \approx 20$, $S_{12} \approx 25$ at $t \approx 20$, $S_{21} \approx 20$ at $t \approx 17.5$, $S_{22} \approx 10$ at $t \approx 12.5$. I_{11}, I_{12}, I_{21}, I_{22} converge at $t \approx 2.5$ and linearly moves upward. The R_{11}, R_{12}, R_{21}, R_{22} are coming closer for different initial values and showing that these will converge at $t > 20$.

For value-3, $S_{11} \approx 45$ at $t \approx 15$, $S_{12} \approx 25$ at $t \approx 15$, $S_{21} \approx 20$ at $t \approx 10$, $S_{22} \approx 15$ at $t \approx 10$. I_{11}, I_{12}, I_{21}, I_{22} converges at $t \approx 2$ and linearly moves upward. The R_{11}, R_{12} coming more closer for different initial values and showing that these will converge at $t > 20$. R_{21} and R_{22} are seen convergent around $t = 20$.

For value-4, $S_{11} \approx 50$ at $t > 12.5$, $S_{12} \approx 30$ at $t \approx 10$, $S_{21} \approx 20$ at $t \approx 7.5$, $S_{22} \approx 15$ at $t \approx 7.5$. I_{11}, I_{12}, I_{21}, I_{22} converges at $t \approx 1.5$ and linearly moves upward. The R_{11} showing to get converged at $t > 20$, R_{12}, R_{21} and R_{22} are seen convergent at $t \approx 17.5$, $t \approx 5$ and $t \approx 2.5$ respectively.

From the above discussions, it can be inferred that there is a strong relationship among nutritional status, immunity, and COVID-19. The different states of nutritional status along with different states of immunity show the changes in susceptibility, infected, and recovered cases in a different way. These changes are evident for the values mentioned in Table 1 only. There can be different sets of parameter values and for a change in parameter values the plots will be different. Besides the parameters related to nutritional status and immunity, our designed model consists of parameters that contribute in the results. The results are sensitive towards those parameters as well. So, change in other parameter values will also change the plots and it will show the effect of nutritional status and immunity in a different way.

5 Conclusions

Though COVID-19 infected a huge population globally, the fatality was not that much high. Most of the fatalities could be found in patients suffering from chronic and critical diseases. This is because of their nutritional status and immunity of the body that got affected for a long time suffering from those diseases. The types of fatal cases indicated towards a relationship among nutritional status, immunity, and COVID-19. So, we formulate a mathematical model considering all possible combinations of immunity and nourishment status along with other related parameters. Mathematical simulation of the model depicts a strong impact of nourishment status and immunity on susceptibility and a considerable impact on infection as well as recovery of COVID-19. From this study, importance of immunity and nutrition is evident and it is mention worthy that maintenance of good immunity and adequate nutrition in the body will significantly reduce the susceptibility, reduce the possibility of infection, and increase the possibility of recovery. Though this model has been used only to study COVID-19 cases, it is possible to apply in other COVID-19-like diseases with required modification for that particular disease.

Declarations

Conflict of interest The authors declare no competing interests.

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