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Original Research

An extended Susceptible-Exposed-Infected-Recovered (SEIR) model with vaccination for forecasting the COVID-19 pandemic in Sri Lanka

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Abstract

Background: After declaration of a Public Health Emergency of International Concern (PHEIC) by the World Health Organization, Novel Corona Virus had been spreading throughout the world despite various degrees of movement restrictions and availability of multiple safe and effective vaccines. Vaccination rate against COVID-19 is one of the infection rate's main determinants. The role of modelling in predicting the spread of an epidemic is important for health planning and policy making.

Objective: This study aimed to construct a compartmental epidemiological model incorporating vaccination coverage, vaccination rate, vaccine efficacies and applied a computational tool for predicting the evolution of different epidemiological variables for COVID-19 in Sri Lanka.

Methods: We used a dynamic Susceptible-Exposed-Infected-Recovered-Vaccinated (SEIRV) model and simulated potential vaccine strategies under a range of epidemic conditions. The predictions were based on different vaccination coverages (5% to 90%), vaccination-rates (1%, 2%, 5%) and vaccine-efficacies (40%, 60%, 80%) under different R_0 (2,4,6). We estimated the duration, exposed, and infected populations.

Results: When the R_0 was increased, the days of reduction of susceptibility and the days to reach the peak of the infection were reduced gradually. At least 45% vaccine coverage is required for reducing the infected COVID-19 population to mitigate a disastrous situation in Sri Lanka.

Conclusion and recommendations: The results revealed that when R_0 is increased in the SEIRV model along with the increase of vaccination efficacy and vaccination rate, the population to be vaccinated is reducing. Thus, the vaccination offers greater benefits to the local population by reducing the time to reach the peak, exposed and infected population through flattening the curves. The prediction models will lead to policy relevance despite the significant uncertainty associated with real-time forecasting in complex systems with timely predictions and steadfast reports.

Keywords: COVID-19; SEIRV model; Vaccine efficacy; Vaccination rate

Introduction

Background

After declaration of a Public Health Emergency of International Concern (PHEIC) by the World Health Organization (WHO), Novel Corona Virus had been spreading throughout the world despite various degrees of movement restrictions and availability of multiple safe and effective vaccines [1]. According to the Weekly epidemiological update on COVID-19 on 11th May 2021, there was a 4% reduction of the number of new COVID-19 cases and deaths globally, with over 5.5 million cases and over 90,000 deaths for the past week. Although there was a 13% reduction of the newly reported weekly caseload in the Eastern Mediterranean and a 23% reduction in Europe regions, South-East-Asia (SEA) shows upward trends for the 9th consecutive week, which reported a further 6% increase as of 9th May 2021. Further, new deaths were increasing in SEA (15%) and Africa (3%), while India remained the primary concern as the contributing country for half of the global cases and nearly one-third of global deaths [2]. Similar to the regional situation, the number of cases was rising in Sri Lanka, with 2375 per day (14th to 19th May 2021). A total of 147,720 individuals were confirmed as infected by May 19, 2021 [3,4]. Strain B.1.1.7 was a more transmissible variant that was initially detected in the United Kingdom (UK), was circulating in Sri Lanka at that time [5]. Therefore, early understanding of the epidemic and demand dynamics was fundamental in health planning and policymaking, especially when the resources are limited.

Compartmental models for prediction

Compartmental models can be used to project scenarios with various disease control measures individually or as a useful combination for evidence-based policy formulation and alteration. With the purpose of forecasting, different forecasting models were proposed by various academics and research groups. However, these forecasting models had their strengths and limitations. Therefore, they need to be interpreted cautiously. Furthermore, the underlying data were changing rapidly [6,7]. There were broad categories of mathematical models for COVID-19 forecasting, such as mass action compartmental models, structured metapopulation models and Agent-Based Network Models. Epidemiologists have been using mass action compartmental models over a period of hundred years which are famous for simplicity in both analysis and outcome assessment [8]. Importantly, from early December 2020, mass vaccination programs were started against the COVID-19 pandemic. Pfizer/BioNTech, Oxford/AstraZeneca, Janssen, Moderna and Sinopharm vaccines were included in the WHO Emergency Use Listing (EUL) and were widely used globally [9]. By 19th May 2021, 9.35% of the world population had received at least one dose of the COVID-19 vaccine and 1.56 billion vaccine doses were already administered globally [10,11]. In Sri Lanka, 1,397,999 individuals (2.6% of the population) were vaccinated by at least one dose of vaccine out of Covishield, Sinopharm or Sputnik-V vaccines through mass vaccination programmes [3,12]. More importantly, public health interventions successfully limited the initial rapid transmission of COVID-19 in many countries. However, the epidemic recrudescence could occur due to the relaxation of these measures without achieving elimination or high levels of herd immunity risks [13].

SEIR model and extensions

Several compartmental models belong to the basic Susceptible-Infectious-Recovered (SIR) class. In the SIR model, the total population (N) is divided into compartments of Susceptible (S), Infectious (I) and Recovered (R). The SIR models are extended to SEIR models by adding an Exposed (E) compartment based on the same principle. It is assumed that every individual in the population is going through those four roles from susceptibility

to recovery [Susceptible (S)-> Exposed (E)-> Infected (I)-> Recovered (R)]. Although real-life situations have some limitations, this has been used as a basic model for different epidemics [8,14]. Due to the proven effect of prevention of infection by vaccination, Vaccination (V) was also included in the SEIR model, and the Susceptible-Exposed-Infected-Recovered-Vaccinated (SEIRV) forecasting model is formulated.

Vaccination rate, vaccination coverage, vaccine efficacy, and effectiveness of the vaccination

Vaccination rate against COVID-19 is one of the infection rate's main determinants (along with the vaccine efficacy and effectiveness). It should be considered with the other factors related to the spread of the disease, such as adherence to preventive measures. Reduced infection rates begin with varying vaccination rates across countries. It has been observed that the infection rate after vaccination shows two trends including an 'inverted U-shaped trend' and a 'L- shaped trend' [15]. Sri Lanka started Covishield (AstraZeneca) as the COVID-19 vaccine for the country's vaccination programme from 29th January 2021 [16]. Even though the efficacy data of the different COVID-19 vaccines vary in different global studies, there should be a minimum of 50% efficacy for the WHO emergency use licensing of a COVID-19 vaccine [17]. Further, the efficacy of the same COVID-19 vaccine can vary with the variant of the virus that depends on the vaccine schedule. For instance, it could be whether only the first dose was taken or whether the person completed the schedule [18]. It was found that the effectiveness of the Covishield (AstraZeneca) vaccine after the first dose was 76% (95% CI: 61-85%) and 86% (95% CI: 53-96%) following the completion of both doses against the alpha variant (B1.1.7) which was the predominant variant in Sri Lanka during the study period [19].

Aim of the study

The present study aimed to construct a compartmental epidemiological model incorporating vaccination coverage, vaccination rate, vaccine efficacies and applied a computational tool for predicting the evolution of different epidemiological variables for COVID-19 in Sri Lanka to contribute to policymaking. We applied a dynamic SEIRV model for this purpose. The predictions were based on the SEIRV model without vaccination, evolution of infectious proportion under different vaccination coverages (5% to 90%), vaccination rates (1%, 2%, 5%) and vaccine efficacies (40%, 60%, 80%) at different R_0 (2,4,6). The model was used to estimate the duration and infected population following different vaccination coverages.

Method

Compartmental epidemiological model

We constructed a compartmental epidemiological model (Figure 1) with vital dynamics describing the number of individuals in a fixed population who are susceptible to infection (S), exposed (E), infected (I), recovered (R), and vaccinated (V) [8,14]. This simple deterministic model has several structural assumptions, including homogenous mixing of a closed population, no stratification of transmissibility by subpopulations, and complete and permanent immunity after natural infection.

A set of ordinary differential equations governs the flow of individuals between compartments. We extracted publicly available data with permission from the official website of the Health Promotion Bureau of the Ministry of Health, Sri Lanka. The data was cross-checked with the daily update on the website of the Epidemiology Unit, Ministry of Health, Sri Lanka [3,4]. We used anonymized data for this analysis and extracted data relevant to cases reported from 11th March 2020 to 15th May 2021. Based on reported cases and the documented parameters, the model was validated for its ability to predict the number of cases for a period of 14 days in February 2021

and model fitting is illustrated in Supplementary file I (S1 File).

Any personally identifiable data was not included in the analysis of this study. Python programming language was used for the development of the model. We have considered three hypothetical values for R_0 [Basic reproduction number, 'New infections generated by each infectious individual in a susceptible population without transmission reduction measures']. Predictions for the SEIRV model were made when the Ro value is 2, 4 and 6. Parameter beta (β) represents the transmission rate of the COVID-19. As one of the main assumptions, we assumed that the transmission rate β for both the susceptible and vaccinated populations is equal during the model development stage.

Model equations

The flow of individuals through the compartments of the model is determined by a set of Ordinary Differential Equations (ODE). The time-variant parameters such as rate of change of susceptible population, exposed population, infected population, recovered population and vaccinated population is obtained by derivates with the following equations. Given the SEIRV model with transition forces, the ODEs are derived as below.

$$\frac{dS}{dt} = -\beta I \left(\frac{S}{N}\right)^{\alpha} - \delta\varepsilon S \quad (1)$$

$$\frac{dE}{dt} = \beta I \left(\frac{S}{N}\right)^{\alpha} + \beta I \left(\frac{V}{N}\right)^{\alpha} - \sigma E \quad (2)$$

$$\frac{dI}{dt} = \sigma E - \gamma I \quad (3)$$

$$\frac{dR}{dt} = \gamma I + \varsigma V \quad (4)$$

$$\frac{dV}{dt} = \delta\varepsilon S - \beta I \left(\frac{V}{N}\right)^{\alpha} - \varsigma V \quad (5)$$

Disease characteristics

The available COVID-19 data was used as the disease characteristics in this exploration (Table 1). However, there is still substantial uncertainty around these estimates and how they apply to a given setting, and there are insufficient data on which to base credible parameter distributions.

Mass vaccination programme

We modelled an indiscriminate mass vaccination programme where 13,151 individuals received their first dose of vaccine against COVID-19 during the first 100 days of the vaccination campaign in Sri Lanka (as would be expected in the absence of a reliable and scalable method of determining either pre-existing immunity or active or incubating infection) [3]. The model parameters are presented in Table 2.

Vaccination coefficient in the model

A combination of 'vaccination efficacy' and 'vaccination rate' is known as 'vaccination coefficient' in the model. Notably, the vaccination efficacy and vaccination rate are determined by the health authorities. When the R_0 and rate of vaccination are constant and vaccination efficacy is increased (40%, 60% and 80%), the vaccination coefficient will be increased in line with the increased efficacy. Therefore, it implies that the increase of vaccination coefficient would increase the vaccinated population while reducing the exposed and infectious population to reach its maximum within a lesser number of days. Moreover, when the R_0 is constant, vaccination efficacy and rate of vaccination are increased, the vaccination coefficient is also increased. Therefore, the number of vaccinated populations from the susceptible population is also increased. As a result, the number of exposed, infectious populations decline and reach the equilibrium level in the early days in the graphs, which indicates that the COVID-19 crisis can be controlled if we increase the efficacy and rate of vaccination. Under a lower level of vaccination coefficient, the equilibrium comes in later days of the graphs while it increases the exposed and infectious populations.

Results

As in a pandemic like COVID-19, a compartmental model is a good approach for comprehension and analyzing epidemiological data. However, the model needs to be adjusted to consider specific aspects of the epidemic under analysis [25]. First, we predicted the SEIRV model dynamics without vaccination. Thereafter, the predictions were based on, evolution of infectious proportion under different levels of vaccination coverages (5%, 15%, 30%, 45%, 60%, 75%, 90%), SEIRV under different levels of vaccine efficacies (40%, 60%, 80%) with the current rate at different R_0 and SEIRV under combined co-efficient (vaccine rate x vaccine efficacy) different levels of vaccination rates (1%, 2%, 5%), different vaccine efficacies (40%, 60%, 80%) and different R_0.

Prediction based on the SEIRV model without vaccination.

We observed how SEIR dynamics are affected without vaccination for COVID-19 at a specific time in the system's evolution with different R_0 values. When the R_0 equals 4, the susceptibility will be reduced around 75 days. Thus, the number of days to reach the peak of the infection curve will be 105 days. In addition, approximately 6.2 million individuals will be infected at the peak of the infection curves, respectively. Thus, around 3 million individuals in 90 days will be exposed at the peak of the exposed curves. Furthermore, the susceptible curve crosses with the recovered curve in 95 days with 6 million individuals. Moreover, the susceptible curves stabilize around 115 days with susceptible 0.1 million individuals. Furthermore, the recovered curves stabilize with 21.8 million around 125 days (Refer Figure 2 and S1 Table).

Evolution of infectious proportion under different levels of vaccination coverage

Using the SEIRV model, we predicted the proportion of the infected population for the different vaccination coverages taking into account the vaccination rate of the first 100 days in Sri Lanka (Per day vaccination rate=0.06%). According to the findings, if there are 5%, 15%, 30%, 45%, 60%, 75% and 90% vaccination coverages, the time of reaching the peak proportion of the infected individuals will be reduced by 40, 30, 25, 22, 21, 20 and 19 days respectively (Table 3). Moreover, after 45% vaccine coverage of the susceptible individuals, there will be a relatively slow reduction of peak reach for the proportion of the infected population. Therefore, at least 45% fully vaccine coverage will be adequate for reducing the infected population to control the outbreak since there is no prior immunity in the local community.

Evolution of SEIRV under different vaccine efficacies and R_0 of 4 with per day vaccination rate of 0.06% (First 100 days)

We observed how the dynamics of SEIR are affected by vaccination for COVID-19 at a specific time in the system's evolution in the first 100 days after initiation of the vaccination campaign in Sri Lanka. As a result, vaccines with different efficacies as a response strategy applied to the COVID-19 epidemic was assumed at R_0 value of 4.

R_0=4; Efficacy= 40%, 60%, 80% with per day vaccination rate 0.06%

When R_0 is equal to 4, with 40%, 60% and 80% vaccine efficacies at the current rate of vaccination (0.06% per day), 79,943, 119,144 and 157,852 individuals can be vaccinated in 50 days, and the susceptibility will be reduced around 65, 70 and 75 days respectively. Thus, the number of days to reach the peak of the infection curve will be 105, 110 and 115 days, and 5 million, 4.5 million and 4 million individuals will be infected at the peak of the infection curves, respectively. Furthermore, 2.5 million individuals in 90 days, 2 million individuals in 95 days and 1.5 million in 100 days will be exposed at the peak of the exposed curve, respectively. Correspondingly, the susceptible curve crosses with the recovered curve in 90 days with 5 million, in 95 days with 6

million and 6.5 million populations in 100 days. Moreover, the susceptible curves stabilize around 125 days with 0.5 million, 120 days with 0.4 million individuals and 115 days with susceptible 0.25 million individuals (Figure 3; S2 Table).

Evolution of SEIRV under different vaccine efficacies (40%, 60%, 80%) and different per day vaccination rates (1%, 2%, 5%)

The SEIRV predictions were performed for the different COVID-19 vaccine efficacies and the vaccination rates (per day) of 1%, 2% and 5% (Fig 4).

R_0=4; Efficacy= 40%; Vaccination rates of 1%, 2% and 5%.

When R_0 is 4 with vaccine efficacy of 40% and vaccination rates of 1%, 2% and 5%, 1.03 million, 1.86 million and 3.74 million individuals can be vaccinated in 35 days, 35 days, and 25 days respectively. Moreover, 3.11 million, 0.81 million individuals and 1,478 individuals will be infected at the peak of the infection curves, and 1.36 million, 0.33 million, and 589 individuals will be exposed at the peak of the exposed curves, respectively. Furthermore, the susceptible curves cross the recovered curve in 105 days, 90 days, and 35 days, respectively (Figure 4a; S3 Table).

R_0=4; Efficacy= 60%; Vaccination rates of 1%, 2% and 5%.

When R_0 is equal to 4 with the efficacy of 60%, 1.47 million, 2.57 million and 4.9 million individuals can be vaccinated in 30 days, 28 days, and 20 days respectively. If there is a 1% vaccination rate, the number of days to reach the peak of the infection curve will be 125, and 1.8 million individuals will be infected at the peak of the infection curve, and 53,773 and 91 will be infected with 2% and 5% vaccination rates respectively. In addition, at the peak of the exposed curves, 0.76 million individuals, 21,041 individuals, 225 individuals will be exposed with 1%, 2% and 5% rates, respectively. Furthermore, the susceptible curves cross with the recovered curve in 100 days, 65 days, and 30 days with 10 million individuals (Figure 4b; S3 Table).

R_0=4; Efficacy= 80%; Vaccination rates of 1%, 2% and 5%.

When the vaccine efficacy is 80% with the vaccination rates of 1%, 2%, and 5%, 1.86 million individuals, 3.19 million individuals and 5.87 million individuals can be vaccinated in 35 days, 25 days, and 20 days. Moreover, 0.81 million individuals in 135 days, 5,883, and 84 individuals will be infected at the peak of the infection curves, respectively. Furthermore, 0.33 million individuals in 130 days, 2,321 and 35 individuals will be exposed at the peak of the exposed curves. The susceptible curves cross with the recovered curve in 90 days, 40 days, and 25 days respectively, around 8 million individuals (Figure 4c; S3 Table).

Discussion

Predictive models have taken on a newfound importance in response to the spread of the COVID-19 pandemic and causative agent [26]. There are widespread public discussions on COVID-19 based on the features of epidemiological curves. For understanding the dynamics of the pandemic and assessing the effects of various intervention strategies, the epidemiological models and their graphical representations are valuable tools. However, the parameters may be affected by the inadequate explanations of these models' representations, usefulness, and inherent limitations. Notably, accurate public interactions and communications are vital during any disastrous situation like the COVID-19 global pandemic. Moreover, explaining the current circumstances, actions, and intended outcomes is a timely need to gain the support and cooperation of the public and stakeholders to manage the critical situation, prevent the spreading of fake news, and minimize voluntary compliance [27].

The compartmental models were invented during the late 1920s, which are the most commonly used models in epidemiology.

Moreover, different approaches using agent-based simulations are still founded on those basic models [25]. The SEIR model is frequently used to explain the COVID-19 pandemic, which is fundamental and a reasonably good fit for this disease [14]. However, during the COVID-19 pandemic, the number of deaths has often been highly inaccurate for many reasons, and the number of infected has also been incorrect. There can be undiagnosed cases during that period because of limited testing, which lead to inaccurate reporting [25,28]. The type of model is an extension of SEIR with the intervention of vaccination. The proposed model uses the predictors as in the parameter table (Table 2). The model was built based on the conceptual framework developed with the predictor selection. Moreover, due to the static nature of the parameters, which does not reflect any internal or external change during the epidemic is a limitation of these models [8,28]. Furthermore, the predictive capability of the tool is highly dependent on several preliminary data for parameter estimation. Notably, an essential parameter in epidemic modelling is the 'basic reproduction ratio/ratio (R_0)', which is the 'expected or average number of individuals an infected person subsequently infects'. The size of the R_0 can be varied since it is determined by averaging many cases [25]. With the constant R_0, increase vaccination efficacies, and increased rate of vaccinations lead to increased vaccination coefficient. Therefore, it leads to an increased number of vaccinated populations from the susceptible population. As a result, the number of exposed, infectious populations are reduced and reach the equilibrium level at early days in the prediction graphs, which indicates that the COVID-19 crisis can be reduced if we increase the vaccine efficacy and the rate of vaccination. Under a lower level of vaccination coefficient, the equilibrium comes in later days of the prediction graphs while it increases the exposed and infectious populations. Therefore, we must give more attention to bring more efficient vaccines for COVID-19, and the rate of the vaccination campaigns need to be improved as a disaster mitigation strategy. Theoretically, R_0 is varied, which estimates the speed at which a disease can spread in a population. Therefore, the R_0 is increased in the SEIRV model along with the increase of the vaccination efficacy. Moreover, the population to be vaccinated is also decreased for respective R_0. Furthermore, when R_0 is increased in the SEIRV model along with the increase of both vaccination efficacy and vaccination rate, the population to be vaccinated is also declined. Hence, the vaccination offers the greatest benefits to the local population by reducing the time of peak arrival and infected population.

In addition, the infection fatality ratio (IFR) of COVID-19 acts as a simple factor in the mortality effects of vaccination and does not alter the relative conclusions. The IFR estimates this proportion of deaths among all infected individuals. There are limited serological studies to calculate IFR accurately during outbreaks. In such situations, estimates need to be made with routinely available surveillance data, which generally consist of time series of cases and deaths reported in aggregate [29]. When considering the available data, it is almost similar to the study in China [21]. During the first 10 to 12 months, the mitigation policies reduced overall cumulative mortality without necessarily relying on the emergence of an effective vaccine. The model presented in this study revealed that the overall benefit of vaccination of a population is helping to suppress the epidemic curve by minimizing infected populations. However, the local benefits deteriorate with any additional prolongation of the vaccine development process and delaying availability. When transmission slows due to accumulated population immunity derived from infection, the benefit of vaccination needs to be assessed by conducting proper post-vaccination trials [30,31]. Moreover, the public health measures strongly influence the feasibility

of vaccine trials during a COVID-19 epidemic. Although high background risk of infection results in reduced marginal risks to participants, a substantially greater public health benefit results in low background risk during the period before vaccine availability [31,32].

Conclusion and Recommendation

The results revealed that when R_0 is increased in the SEIRV model along with the increase of vaccination efficacy and vaccination rate, the population to be vaccinated is reducing. Thus, the vaccination offers greater benefits to the local population by reducing the time to reach the peak, exposed and infected population through flattening the curves. The prediction models will lead to policy relevance despite the significant uncertainty associated with real-time forecasting in complex systems with timely predictions and steadfast reports. Thus, the proposed model can serve as a tool for health authorities for planning and policymaking to control the pandemic by cost-effectively implementing appropriate vaccination campaigns.

Limitations

The predictors of the SEIRV compartmental model have been analyzed using ODEs. The model predicts the plausible parameters with the robust estimation within the limitations. One of the significant limitations of the model is that it does not include the natural death and birth rates assuming those are constant [28,31]. Internal and external validation of the model is vital for the robust prediction of the ODEs in the model. Thus, the models were applied in the series of equations to get the equilibrium in the SEIRV model. Then, the simulation of the validated model was performed to obtain the policy scenarios of the proposed model. Usually, the SEIR model consists of initial parameters, which predicts as those are applied to the model precautionary [30,32]. Initially, the model comprises one exposed individual, and the rest of the population is considered a susceptible population [33,34]. Therefore, the predictors were handled with care in the model to avoid overestimation or underestimation. Second limitation was, we did not estimate the reproductive ratios from data in a particular population which is useful for that population. However, the parameters such as vaccination efficacy and vaccination rate can be adjusted according to the implementation of preventive strategies. Thirdly, with the availability of limited similar studies, prediction results difficult to compare and discuss. It is also a limitation factor for the study.

Author declaration

Author contributions: All authors contributed to the conceptualization and design of the study. The formal analysis was done by SPJ (Software), RMNUR and TKT (Re-analyzed with same data set to improve the quality). The original draft preparation was done by RMNUR. IG, PCW and SB contributed to manuscript preparation and finalization. The manuscript was reviewed by MSDW, SPJ, TKT, and YA. All authors read and approved the final manuscript.

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Table 1: Disease characteristics

Parameter	Modelled value	Reference
R_0	2, 4, 6	Assumed
The latent period prior to infectivity	3.2 days	[20]
Duration of infectivity	8.5 days	[1, 9]
Time from infection to death	22 days	[21]
Infection Fatality Ratio (IFR)	0.66%	[2, 21]

Table 2: Values for the model parameters corresponding to the Sri Lankan COVID-19 situation

Parameter	Definition	Value	Units	Reference
N	Population 'Number of individuals in the population'	21,919,000	number	[22]
S	Susceptible 'Individuals in the population not infected, vaccinated, or immune'	21,919,000 – 1 =21,918,999	number	
E	Exposed 'Individuals infected but not yet infectious'	1 (on day 1)	number	Assumed
I	Infected 'Individuals able to transmit infection'	0 (on day 1)	number	
R	Recovered 'Individuals neither infectious nor able to be infected'	0 (on day 1)	number	
V	Vaccinated 'Vaccinated individuals who have not yet achieved protective immunity'	0 (on day 1)	number	
R_0	Basic reproduction number 'New infections generated by each infectious individual in a susceptible population without transmission reduction measures'	2.53	dimensionless	[20]
α	Abrogation of infectivity as the susceptible fraction falls	1.2a	dimensionless	[23,24]
β	Transmission coefficient from infected individuals ($R_t.\gamma$)	Derived	day^{-1}	
γ^{-1}	Infectious period - 'Time from the onset of infectiousness to reversion to non-infectiousness'	8.5 days	day^{-1}	[1,2]
δ	Vaccination rate 'Proportion of the *Susceptible* population undergoing vaccination each day'	0.06%	dimensionless	[3]
ε	Vaccine efficacy 'Relative risk reduction of infection achieved through vaccination'	40%, 60%, 80%	dimensionless	Assumed
η^{-1}	Latent period 'Time from exposure to the development of infectiousness'	3.2 days	day^{-1}	[20]
ς^{-1}	Time to protective immunity after vaccination	21 days	day^{-1}	Assumed
IFR	Infection fatality ratio 'Proportion of all infections that result in death'	0.66%	dimensionless	[21]

Table 3: Relationship between different vaccination coverages with the infected proportion and time of peak arrival

Percentage of vaccine coverage	Proportion infected out of Susceptible (21.9 million)	Time of peak arrival
5%	6.80%	Day 40
15%	2.70%	Day 30
30%	1.80%	Day 25
45%	**1.60%**	**Day 22**
60%	1.50%	Day 21
75%	1.45%	Day 20
90%	1.44%	Day 19

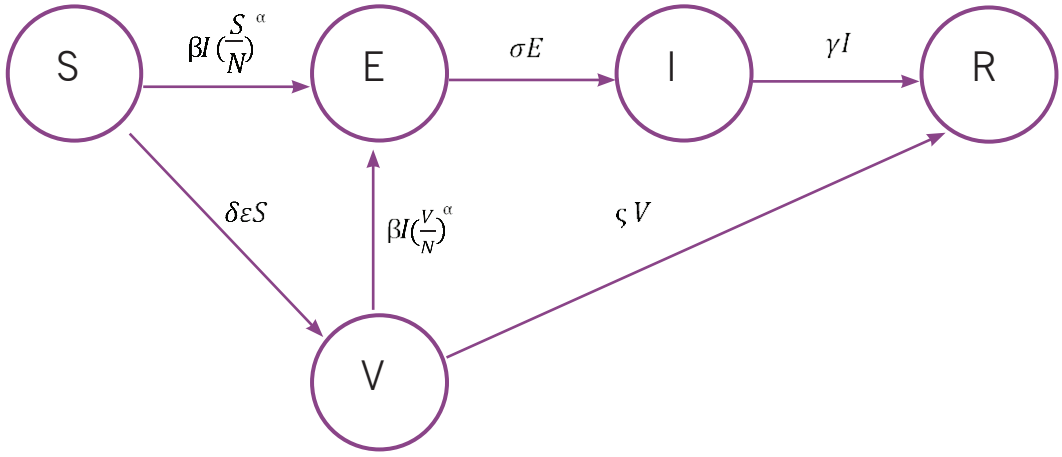


Figure 1: SEIRV Model with Transition Forces

R_0=2 **R_0=4** **R_0=6**

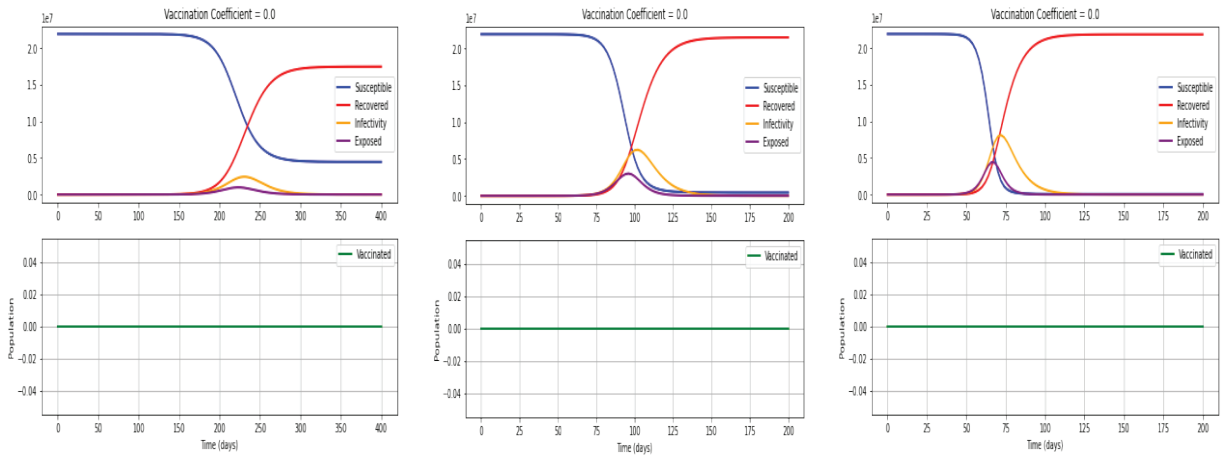


Figure 2: Evolution of infectious proportion without vaccination with different R_0 values

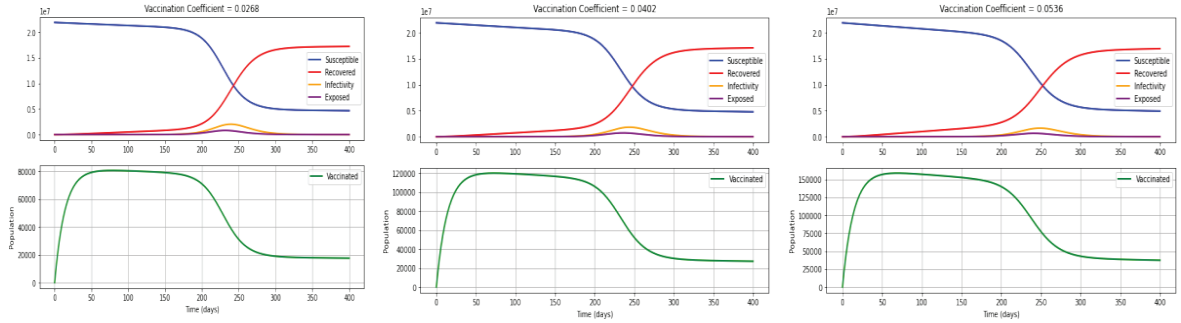
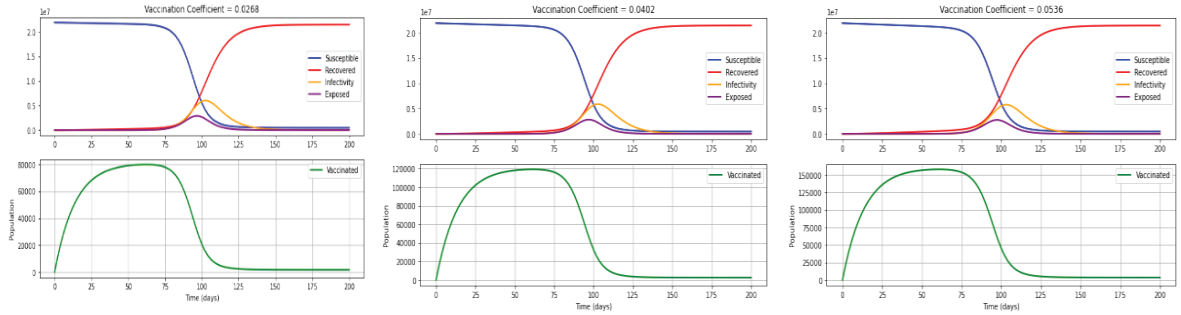
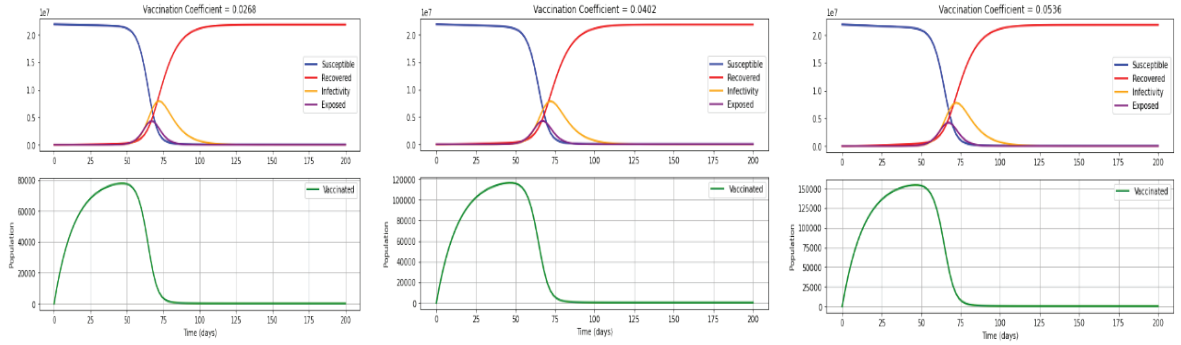
R_0	Vaccine Efficacy		
	40%	60%	80%
2			
4			
6			

Figure 3: Prediction based on the SEIRV model considering the parameter R_0 (R_0=2,4,6) and Vaccine efficacy variation (Vaccine efficacy=40%,60%,80%)

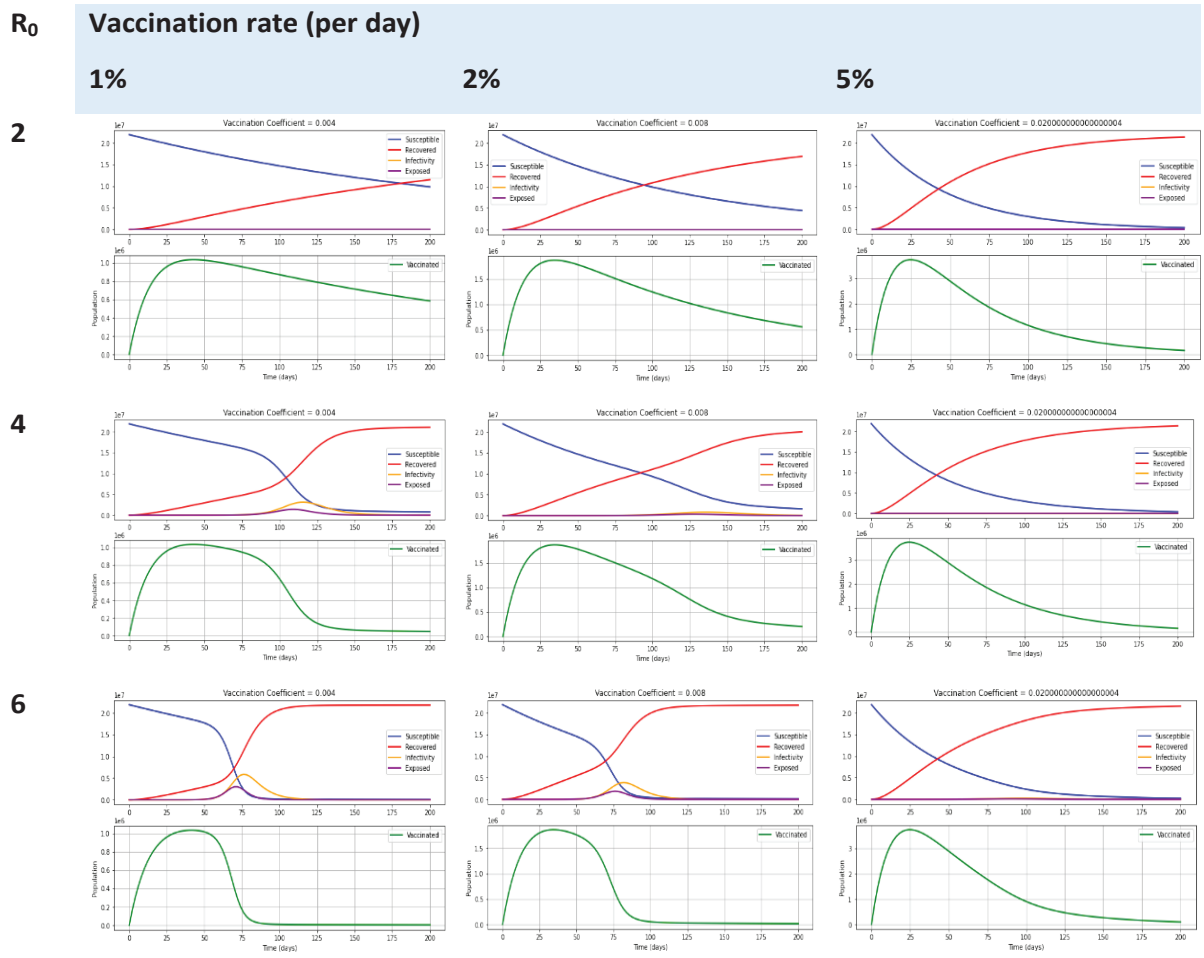


Figure 4a: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), R_0 of 2, 4, 6 with 40% Vaccine efficacy

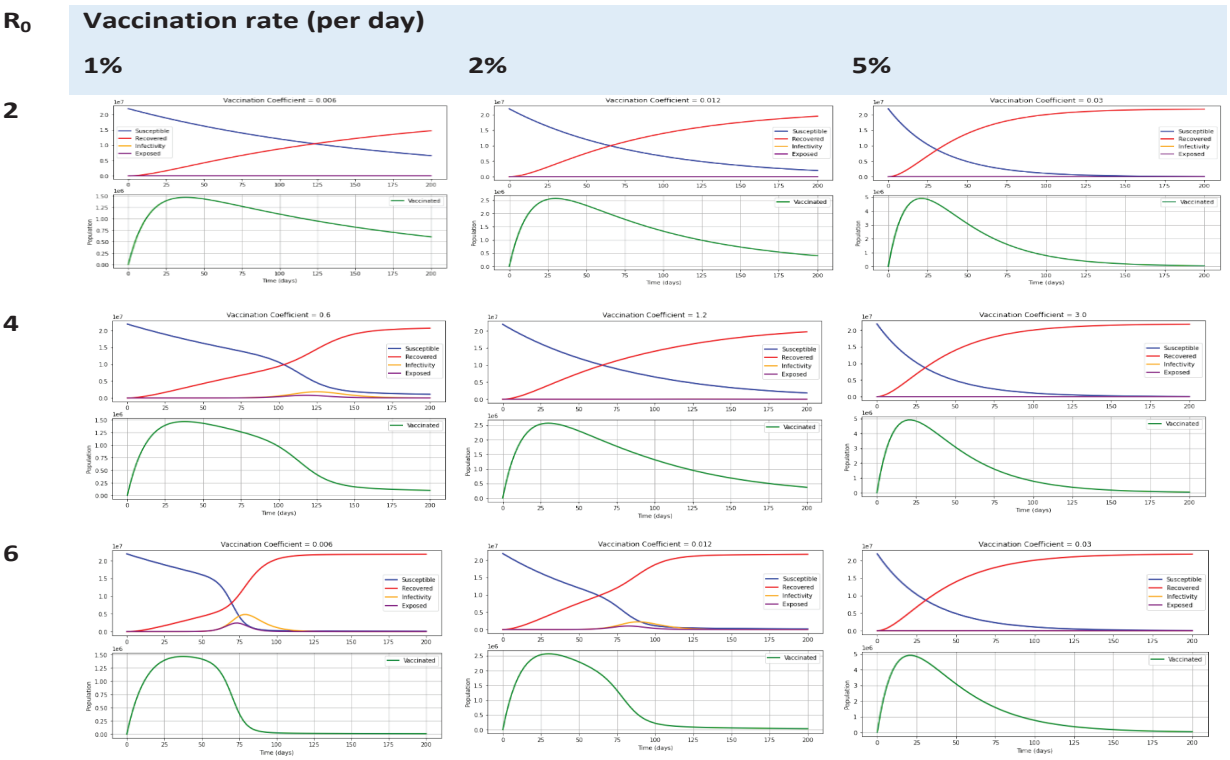


Figure 4b: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), R_0 of 2, 4, 6 with 60% Vaccine efficacy

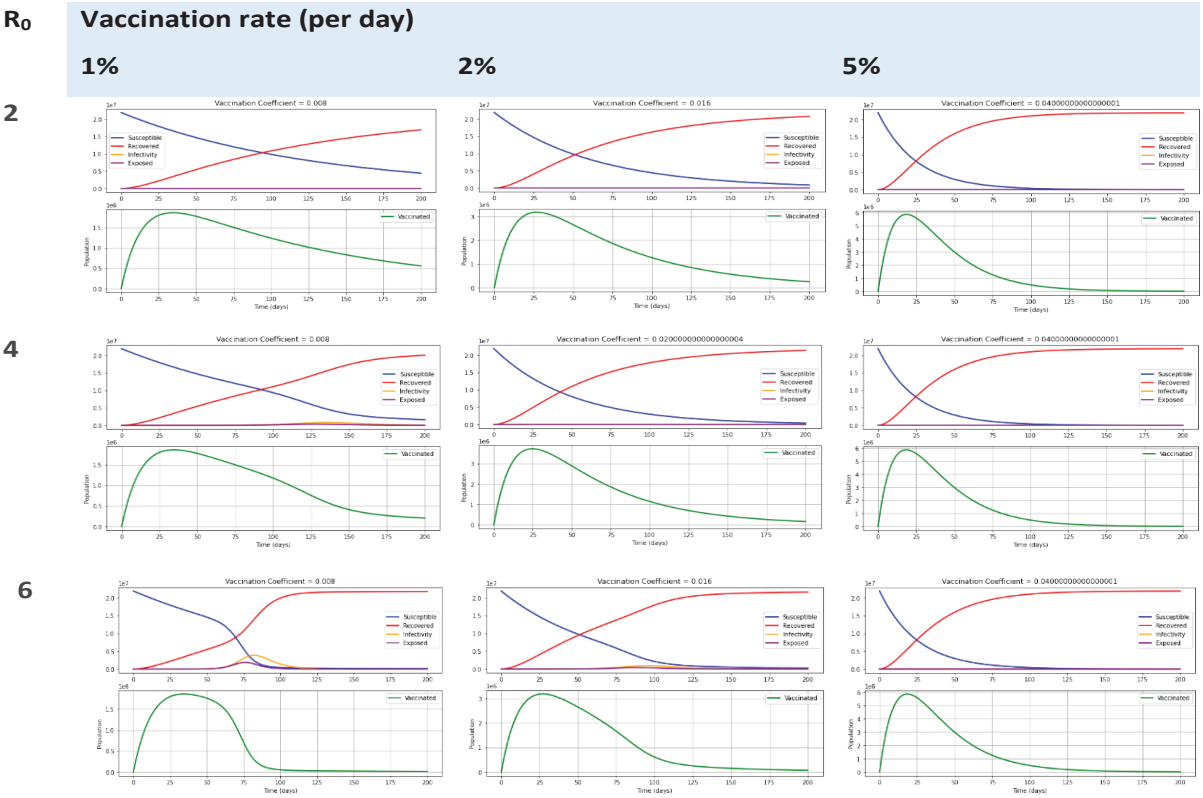


Figure 4c: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), R_0 of 2, 4, 6 with 80% Vaccine efficacy

Supporting Information (Supplementary files)

S1 File. Model validation

Supporting file, one is 'Model validation'

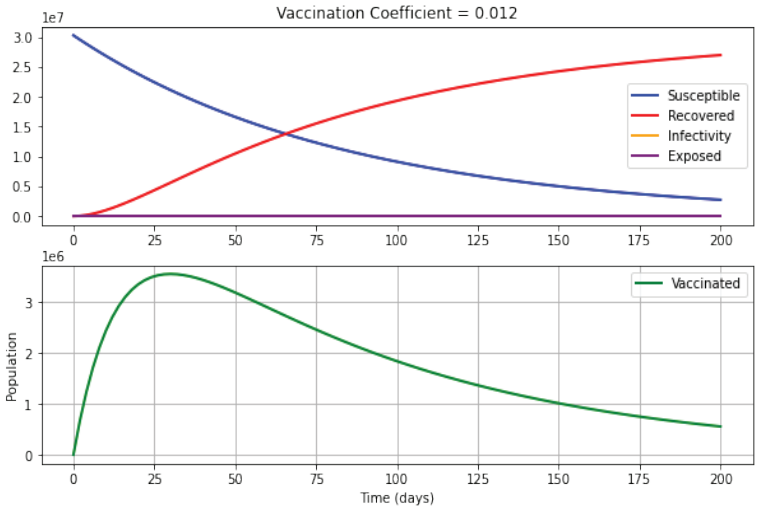
Model Validation

Since the situation of New Delhi, India was similar to the Sri Lankan situation of the COVID-19 during the first quarter of 2021, we used the same data for validating the present SEIRV model. In addition, the time frame of the New Delhi situation is also similar to the Sri Lankan conditions (a parallel time frame). Accordingly, the validation component has supplemented the model that we have used in the analysis. Furthermore, we have considered R_0 of 2, 4, 6 in this analysis.

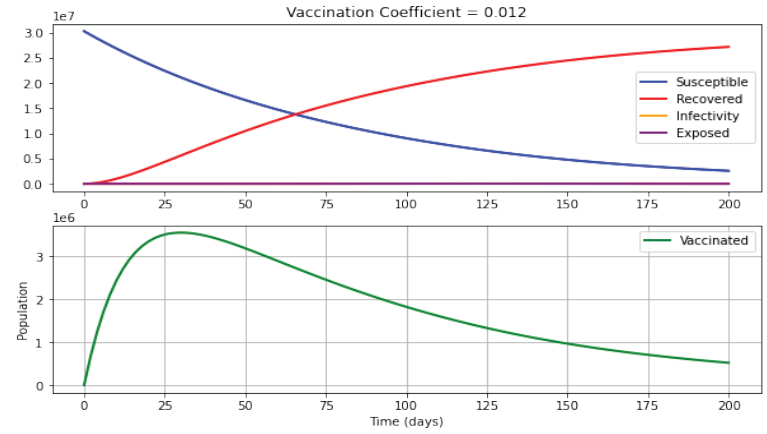
S1. Table 1: Model parameters for validation

Parameter	Value (New Delhi)	Value (Sri Lanka)
Incubation period	5.74	5.5
Hospitalization period	21	22
Population	30,291,000	21,919,000
R_0	2,4,6, (Assumed)	2,4,6, (Assumed)
Vaccination rate 2%	2 %	1%,2%,5%
Vaccine efficacy	60% (Assumed: AstraZeneca)	40%,60%,80%
Social distancing and other policies	0	0
Source: CDC (www.cdc.gov)		

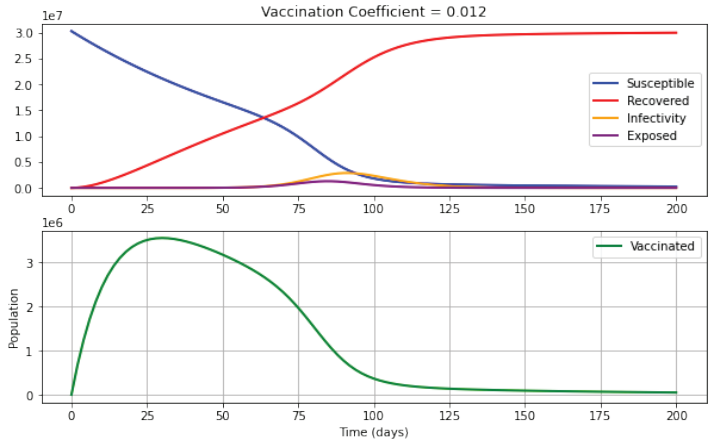
R_0= 2



R_0=4



R_0=6



S1. Table 2: SEIR model validation and simulation for New Delhi in India (Population)

R_0	Infection	Exposure	Vaccinated
2	11	5	3,549,725
4	54,993	21,503	3,549,705
6	2,872,463	1,286,209	3,549,523

S1 Table: Evolution of infectious and exposed population without vaccination

R_0	Vaccination coverage	Exposed population	Infected population
2	0	979,423	2,427,735
4	0	3,019,928	6,248,497
6	0	4,423,387	8,118,512

S2 Table: Evolution of SEIRV under different levels of vaccine efficacies and different R_0

R_0	Vaccine efficacy	Vaccinated population	Exposed population	Infected population
2	40%	80,256	811,368	2,028,917
	60%	119,792	730,670	1,836,608
	80%	158,502	651,930	1,646,643
4	40%	79,943	2,887,652	6,023,035
	60%	119,144	2,814,030	5,898,324
	80%	157,852	2,759,222	5,780,785
6	40%	77,869	4,290,311	7,966,180
	60%	116,289	4,253,997	7,886,468
	80%	154,369	4,218,349	7,804,450

S3 Table: Evolution of SEIRV under different Vaccination rates at R0=2,4,6 with the Vaccine Efficacy of 40%, 60% and 80%

Vaccine efficacy	R_0	Vaccination rate	Vaccinated population	Exposed population	Infected population
40%	2	1%	1,034,457	238	627
		2%	1,862,458	12	31
		5%	3,739,425	4	1
	4	1%	1,034,383	1,369,746	3,114,015
		2%	1,862,427	325,594	807,301
		5%	3,739,416	589	1,478
	6	1%	1,032,464	3,003,732	5,876,928
		2%	1,862,034	1,878,969	3,888,296
		5%	3,739,362	113,954	279,796
60%	2	1%	1,467,069	33	86
		2%	2,568,631	4	11
		5%	4,907,112	1	3
	4	1%	1,467,020	764,680	1,814,842
		2%	2,568,611	21,041	53,773
		5%	4,907,106	225	91
	6	1%	1,466,123	2,417,586	4,823,162
		2%	2,568,430	2,201,900	994,094
		5%	4,907,083	14,420	5,897
80%	2	1%	1,862,458	31	12
		2%	3,186,149	2	6
		5%	5,866,696	1	2
	4	1%	1,862,427	325,594	807,301
		2%	3,186,132	2,321	5,883
		5%	5,866,691	35	84
	6	1%	1,862,034	1,878,969	3,888,296
		2%	3,186,013	402,552	953,785
		5%	5,866,675	2,644	1,101