An Extended Susceptible-Exposed-Infected-Recovered (SEIR) Model with Vaccination for Forecasting the COVID-19 Pandemic in Sri Lanka

Rajapaksha Mudiyanselage Nayani Umesha Rajapaksha[1]

Millawage Supun Dilara Wijesinghe[2]

Kodithuwakku Arachchige Sujith Prasanna Jayasooriya[3]

Balangoda Muhamdiramlage Indika Gunawardana[4]

Weerasinghe Mudiyanselage Prasad Chathuranga Weerasinghe[4]

[1]Senior Registrar in Community Medicine, Health Promotion Bureau, Ministry of Health, Sri Lanka
[2]Consultant Community Physician, Health Promotion Bureau, Ministry of Health, Sri Lanka
[3]Chartered Economist, Innovation for Development Consultants
[4]Registrars in Community Medicine, Health Promotion Bureau, Ministry of Health, Sri Lanka

Corresponding author: drnayani2020@gmail.com;

Postal Address: Dr. R.M.N.U. Rajapaksha, No.157, Jayanthipura, Kurunegala, Sri Lanka

Abstract:

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The role of modelling in predicting the spread of an epidemic is important for health planning and policies. This study aims to apply a compartmental model for predicting the variations of epidemiological parameters in Sri Lanka. We used a dynamic Susceptible-Exposed-Infected-Recovered-Vaccinated (SEIRV) model, and simulated for 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 observed how the above dynamics influenced the SEIRV model without COVID-19 vaccination at different R_0 values, and estimated the duration, exposed and infected populations. 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 population as early as possible. 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.

Keywords: COVID-19; SEIRV model; COVID-19 vaccines

1. Introduction

After 15 months from the Public Health Emergency of International Concern (PHEIC) declaration by the World Health Organization (WHO), Novel Corona Virus is still 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 is slight 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 reduction of the newly reported weekly caseload in the Eastern Mediterranean and Europe regions, South-East-Asia (SEA) shows upward trends for the 9th consecutive week which reported a further six percent increase during last week. New deaths are increasing in SEA and Africa, while India remains 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 is rising in Sri Lanka, with 2375 per day (14th to 19th May 2021). A total of 147,720 individuals are confirmed as infected by May 19, 2021 [3, 4]. Strain B.1.1.7 is a more transmissible variant which was initially detected in the United Kingdom, is currently circulating in Sri Lanka [5]. Therefore, early understanding of the epidemic and demand dynamics is fundamental in health planning and policymaking, especially when the resources are limited.

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 are proposed by various academics and groups. However, these forecasting models need to be used cautiously since they have their strengths and limitations, and the underlying data are changing rapidly [6, 7]. There are broad categories of mathematical models for COVID-19 forecasting, such as mass action compartmental models, structured meta population 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 are included in the WHO Emergency Use Listing (EUL) and widely used globally [9]. By 19th May 2021, 9.35% of the world population has received at least one dose of COVID-19 vaccine and 1.56 Billion vaccine doses are 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 programme [3, 12]. More importantly, the initial rapid transmission of COVID-19 in many countries was successfully limited by public health interventions. However, the epidemic recrudescence could be occurred due to the relaxation of these measures without achieving elimination or high levels of herd immunity risks. Moreover, over 100 SARS-CoV-2 vaccines are currently under development [13].

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 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 there are some limitations in real-life situations, 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 (a derivative of the classic SIR model), and the Susceptible-Exposed-Infected-Recovered-Vaccinated (SEIRV) forecasting model is formulated. The role of modelling in predicting the spread of an epidemic is important. Therefore, the present study aims to construct a compartmental epidemiological model incorporating vaccination coverage, rate of vaccination campaign and vaccine efficacies and applied a computational tool for predicting the evolution of different epidemiological variables for COVID-19 in Sri Lanka. We applied a dynamic SEIRV model for this purpose. The predictions 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 R0 (2,4,6). The model was used to estimate the duration and infected population following different vaccination coverages.

2. Method

2.1 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 and 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 of 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 was illustrated. Any personally identifiable data was not included in the analysis of this study. Python programming language was used for the analysis, and variables in Table 1 included in this model's development. We have considered three hypothetical valves for R_0. Predictions for the SEIRV model were made when the R_o value is 2, 4 and 6 [Insert Figure 1].

2.2 Model equations

The flow of individuals through the compartments of the model is governed by a set of Ordinary Differential Equations:

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

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

$$\frac{dI}{dt} = \sigma E - \gamma I$$

$$\frac{dR}{dt} = \gamma I + \varsigma V$$

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

2.3 Disease characteristics

The available COVID-19 data was used as the disease characteristics in this exploration (Table 1) [2, 3, 9, 15, 16). 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 [Insert Table 1].

2.4 Mass vaccination programme

We modelled an indiscriminate mass vaccination programme ('as would be expected in the absence of a reliable and scalable method of determining either pre-existing immunity or active or incubating infection') where 0.06% of the population received their first dose of vaccine against COVID-19 during first 100 days of the vaccination campaign [3]. The model parameters are presented in Table 2 [Insert Table 1].

3. Results

As in a pandemic like COVID-19, compartmental models are valid approaches for comprehending and analyzing epidemiological data. However, the model need to be adjusted to consider specific aspects of the epidemic under analysis [21]. The predictions were based on the SEIRV model without vaccination, 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 Ro (2,4,6) and SEIRV under combined co-efficient different levels of vaccination rates (1%, 2%, 5%), different vaccine efficacies (40%, 60%, 80%) and different R_0 (2,4,6).

3.1 Prediction based on the SEIRV model without vaccination

There is a period of seemingly exponential growth in infections, followed by a peak, and a decline, with increased recoveries. We observed how these 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 is equal to 2, 4 and 6, the susceptibility will be reduced around 150 days, 75 days and 50 days respectively. The number of days to achieve the peak of the infection curve will be 230 days, 105 days and 74 days respectively. Approximately 2.4 million, 6.2 million and 8.1 million populations will be infected at the peak of the infection curves respectively. Around 0.97 million in 225 days, 3 million in 90 days and 8.1 million populations in 74 days will be exposed at the peak of the exposed curves respectively. Furthermore, the susceptible curve crosses with the recovered curve in 230 days with 10 million populations, 95 days with 6 million populations and 70 days with 4 million populations respectively. Moreover, the susceptible curves stabilize around 260 days with susceptible 4 million populations, 115 days with susceptible 0.1 million populations and 75 days with susceptible 0.05 million populations respectively. Furthermore, the recovered curves stabilize with 15 million around 300 days, 21.8 million around 125 days and 21.85 million populations around 100 days respectively (Figure 2) [Insert Figure 2 and S1 Table].

3.2 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 (0.06%) (Figure 3). According to the findings, if there are 5%, 15%, 30%, 45%, 60% and 75% vaccination coverages, the time of reaching the peak proportion of the infected population will be reduced by the days 40, 30, 25, 22, 21 and 20 respectively. Moreover, after 45% vaccine coverage of the susceptible population, there will be a relatively slow reduction of peak reach for the proportion of the infected population (Table 3). Therefore, at least 45% vaccine coverage will be adequate for reducing the infected population as early as possible [Insert Figure 3 and Table 3].

3.3 Evolution of SEIRV under different vaccine efficacies and different Ro (2,4,6)

There is a period of seemingly exponential growth in infections, followed by a peak, and a decline, with the increased number of recoveries. We observed how these dynamics are affected by vaccination for COVID-19 at a specific time in the system's evolution. A vaccine with different efficacies as a response strategy, applied in response to the COVID-19 epidemic was focused primarily on different R_0 values. When the R_0 is equal to 2, with 40%, 60% and 80% vaccine efficacies at the current rate of vaccination (0.06% per day), 80,256, 119792 and 158,502 populations can be vaccinated in 50 days respectively. The susceptibility will be reduced around 175 days, 160 days and 150 days respectively. The number of days to achieve the peak of the infection curve will be 240 days, 245 days and 250 days respectively. Moreover, 2.5 million, 3 million and 2.5 million populations will be infected at the peak of the infection curves respectively. Furthermore, 1.5 million populations in 230 days, 0.5million populations in 235 to 240 days and 2.5 million in 245 days will be exposed at the peak of the exposed curve respectively.

Furthermore, the susceptible curve crosses with the recovered curve in 240 days with 10 million populations. Moreover, the susceptible curves stabilize with susceptible 5 million in 290 days, 4.5million in 280 days and 4 million populations in 275 days respectively. In addition, the recovered curves stabilize with 16 million, 17 million and 18 million populations respectively with 40%, 60% and 80% vaccine efficacies (Figure 4; S2 Table).

When the 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 populations can be vaccinated in 50 days respectively. The susceptibility will be reduced around 65, 70 and 75 days respectively. The number of days to achieve the peak of the infection curve will be 105, 110 and 115 days respectively. Moreover, 5 million, 4.5 million and 4 million populations will be infected at the peak of the infection curves respectively. Furthermore, 2.5 million populations in 90 days, 2 million populations in 95 days and 1.5 million in 100 days will be exposed at the peak of the exposed curve respectively. Furthermore, 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 respectively. Moreover, the susceptible curves stabilize around 125 days with 0.5 million, 120 days with 0.4 million and 115 days with susceptible 0.25 million populations respectively with 40%, 60% and 80% vaccine efficacies (Figure 4; S2 Table).

When the R_0 is equal to 6, with 40%, 60% and 80% vaccine efficacies at the current rate of vaccination (0.06% per day), 77,869, 116,289 and 154,364 populations can be vaccinated in 40, 50 and 55 days respectively. The susceptibility will be reduced around 45, 50 and 55 days respectively. The number of days to achieve the peak of the infection curve will be 70, 73 and 75 days respectively. Moreover, 7.97 million, 7.89 million and

7.8 million populations will be infected at the peak of the infection curves respectively. Furthermore, 4.29 million populations in 65 days, 4.25 million populations in 70 days and 4.22 million in 75 days will be exposed at the peak of the exposed curve respectively. Moreover, the susceptible curves stabilize around 75 days with 0.1 million, in 80 days with 0.2 million and 85 days with susceptible 0.3 million populations respectively with 40%, 60% and 80% vaccine efficacies (Figure 4; S2 Table) [Insert Figure 4 and S2 Table].

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 flattering the curves. If the vaccination campaign is successfully implemented, this will undoubtedly impact the selection of the R_0 and consequent infection rates in Sri Lanka.

3.4 Evolution of SEIRV under different vaccine efficacies (40%, 60%, 80%) and 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%.

3.4.1 R0=2; Efficacy= 40%; vaccination rates of 1%, 2% and 5%.

When the R_0 is 2 with vaccine efficacy of 40% and vaccination rates of 1%, 2% and 5%, 1.03 million, 1.86 million and 3.74 million populations can be vaccinated in 35 days, 30-35 days and 25 days respectively and the susceptible curves cross with the recovered curve in 180 days, 90 days and 35 days respectively (Figure 5a; S3 Table).

3.4.2 R0=2; Efficacy= 60%; vaccination rates of 1%, 2% and 5%.

When the R0 is equal to 2 with the efficacy of 60% and 1%, 2% and 5% vaccination rate (per day), 1.46 million, 2.57 million and 4.9 million populations can be vaccinated in 30 days, 25 days and 20 days respectively. The susceptible curve crosses with the recovered curve in 125 days, 65 days and 30 days respectively (Figure 5b; S3 Table).

3.4.3 R0=2; Efficacy= 80%; vaccination rates of 1%, 2% and 5%.

When the R_0 is 2 with vaccine efficacy of 80% and vaccination rates of 1%, 2% and 5%, 1.86 million, 3.19 million and 5.87 million populations can be vaccinated in 30-35 days, 25 days and 15 days respectively. The susceptible curves cross with the recovered curve in 90 days, 50 days and 25 days respectively (Figure 5c; S3 Table).

3.4.4 R0=4; Efficacy= 40%; vaccination rates of 1%, 2% and 5%.

When the 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 populations can be vaccinated in 35 days, 35 days and 25 days respectively. Moreover, 3.11 million in 120 days, 0.81 million in 135 days and 1478 populations will be infected at the peak of the infection curves respectively. Furthermore, 1.36 million in 110 days, 0.33 million in 130 days and 589 populations will be exposed at the peak of the exposed curves respectively. The susceptible curves cross with the recovered curve in 105 days, 90 days and 35 days respectively (Figure 5a; S3 Table).

3.4.5 R0=4; Efficacy= 60%; vaccination rates of 1%, 2% and 5%.

When the R_0 is equal to 4 with the efficacy of 60%, 1.47 million, 2.57 million and 4.9 million populations can be vaccinated in 30 days, 28 days and 20 days respectively. If there is a 1% vaccination rate, the number of days to achieve the peak of the infection curve will be 125 and 1.8 million populations will be infected at the peak of the infection curve and 53773, 91 will be infected with 2% and 5% vaccination rates respectively. Around 115 days, 0.76 million populations will be exposed at the peak of the exposed curves with a 1% rate and 21,041, 225 populations will be exposed with 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 (Figure 5b; S3 Table).

3.4.6 R0=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, 3.19 million and 5.87 million populations can be vaccinated in 35 days, 25 days and 15-20 days. Moreover, 0.81 million in 135 days, 5883 and 84 populations will be infected at the peak of the infection curves respectively. Furthermore, 0.33 million in 130 days, 2321 and 35 populations will be exposed at the peak of the exposed curves respectively. The susceptible curves cross with the recovered curve in 90 days, 40 days and 25 days respectively around 8 million populations (Figure 5c; S3 Table).

3.4.7 R0=6; Efficacy= 40%; vaccination rates of 1%, 2% and 5%.

When the R_0 is 6 with vaccine efficacy of 40% and vaccination rates of 1%, 2% and 5%, 1.03 million, 1.86 million and 3.74 million populations can be vaccinated in 35 days, 30-35 days and 25 days respectively. Moreover, 5.88 million in 76 days, 3.89 million in 80 days and 0.28 million populations will be infected at the peak of the infection curves respectively. Furthermore, 3 million in 72 days, 1.88 million in 78 days and 0.11 million populations will be exposed at the peak of the exposed curves respectively. The susceptible curves cross with the recovered curve in 72 days with 7.5 million, 70 days with 8 million and 40 days with 10 million populations respectively (Figure 5a; S3 Table).

3.4.8 R0=6; Efficacy= 60%; vaccination rates of 1%, 2% and 5%.

When the R_0 is equal to 6 with the efficacy of 60% and vaccination rates of 1%, 2% and 5%, 1.47 million, 2.57 million and 4.9 million populations can be vaccinated in 35 days, 30 days, 20 days respectively. The number of days to achieve the peak of the infection curve will be 80 days and 90 days with 1% and 2% rates respectively and 4.8 million, 0.9 million and 5897 populations will be infected at the peak of the infection curve respectively. Around 75 days and 85 days, 2.4 million, 2.2 million and 14,420 populations will be exposed at the peak of the exposed curves respectively. Furthermore, the susceptible curves cross with the recovered curves in 70 days, 65 days and 30 days respectively with 10 million populations each. Moreover, the susceptible curve stabilizes around 85 days, 100 days and 135 days respectively. The recovered curves stabilize in 115 days, 120 days and 150 days respectively (Figure 5b; S3 Table).

3.4.9 R0=6; Efficacy= 80%; vaccination rates of 1%, 2% and 5%.

When the R_0 is 6 with vaccine efficacy of 80% and vaccination rates of 1%, 2% and 5%, 1.86 million, 3.19 million and 5.87 million populations can be vaccinated in 30 days, 25 days and 20 days respectively. Moreover, 3.89 million in 80 days, 0.95 million in 95 days and 1101 populations will be infected at the peak of the infection curves respectively.

Furthermore, 1.88 million in 75 days, 0.4 million in 85 days and 2644 populations will be exposed at the peak of the exposed curves respectively. The susceptible curves cross with the recovered curve in 70 days, 50 days and 25 days respectively (Figure 5c; S3 Table) [Insert Figure 5 a, b, c and S1-3 Tables].

4. Discussion

Predictive models have taken on a newfound importance in response to the spread of the COVID-19 illness and causative agent [22]. 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, their value may be affected by the inadequate explanations of these models' representations, usefulness and inherent limitations. Importantly, accurate public communications are vital during any disaster situation like the COVID-19 global pandemic. Moreover, explaining the current circumstances, actions, and intended outcomes with clarity are a timely need to gain the support and cooperation of the public and stakeholders to manage the critical situation and prevent spreading of the fake news and minimize civil disobedience [23].

The compartment models were invented during the late 1920s, which are the most commonly used models in epidemiology. Moreover, different approaches using agent-based simulations still based on those [21]. The SEIR model is very frequently used to explain the COVID-19 pandemic, which is basic and a reasonably good fit for this disease [14].

Furthermore, the accuracy of the predictions of the epidemiological models depends critically on the quality of the data feed into the model. If the data quality is good, the model can precisely describe the situations. A fitting example would be when accurately estimating the case fatality rate, which requires all cases of the disease and the number of dead [8]. However, during the COVID-19 pandemic, the number of deaths has often been highly inaccurate for many reasons, and the number of infected have also been incorrect. There can be undiagnosed cases during that period because of limited testing, which lead to inaccurate reporting [21, 24].

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 under the methodological section. The model was built based on the conceptual framework developed with the predictor selection. The model was internally validated using the parameters available in the previous studies in the underpinning literature. As with any modelling approach, our findings relate to the assumptions and inputs of the model which lead to a major limitation. The assumptions with the greatest potential effect on our findings are the structural assumptions of a compartmental epidemiological model. Moreover, due to static nature of the parameters, which does not reflect any internal or external change during the epidemic is a limitation of these models [8, 24]. Furthermore, the predictive capability of the tool is highly dependent on a number of preliminary data for parameter estimation. This dependence may lead to data misinterpretation, especially considering the SIR model. Notably, an essential parameter in epidemic modelling is the 'basic reproduction 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 vary, since it is determined by averaging a large number of cases. Moreover, R_0 depends on contagiousness of the pathogen and number of contact of an infected person [21].

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 we present. 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 [20]. When considering the available data, it is almost similar to the study in China [16]. During the first 10 to 12 months, overall cumulative mortality was reduced by the mitigation policies 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 numbers. 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 [25, 26]. Moreover, the public health measures strongly influence the feasibility of vaccine trials during a COVID-19 epidemic. There is a natural tension between the goals of transmission control measures and those of field trial research, because field trials rely on incident infection to demonstrate vaccine efficacy. The magnitude of potential benefits and risks of SARS-CoV-2 vaccine trials, potential benefits of post-trial vaccination campaigns and the marginal risks are influenced by the public health measures, impending disasters and other epidemic conditions. Although high background risk of infection results in reduced marginal risks to participants, a substantially greater public health benefit results where background risk is low during the period before vaccine availability [26, 27]. The predictors of the SEIRV compartmental model have been analysed using Ordinary Differential Equations (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 [24, 26]. 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 [25, 27]. Initially, the model comprises one exposed individual, and the rest of the population is considered a susceptible population [28, 29]. Therefore, the predictors were handled with care in the model to avoid overestimation or underestimation.

Implications

The prediction models with timely predictions and a fast pace of reports will lead to political relevance even with the great uncertainty associated with real-time forecasting in complex systems. New policy discussions need to occur whenever the best available options such as vaccination and knowledge about the epidemiology changes. 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.

5. Conclusion and Recommendation

A computational model for predicting the spread of COVID-19 by dynamic SEIRV model has been proposed. At least 45% vaccine coverage is required for reducing the infected population as early as possible. Theoretically, R_0 of the model is varied and is uncontrollable. However, the parameters such as vaccination efficacy and vaccination rate can be adjusted. When R_0 is increased in the SEIRV model along with the increase of the vaccination efficacy, the population to be vaccinated is also decreased for respective R_0 even it needs to maintain the population exposed and the infected population are decreasing. Moreover, 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 reducing. Hence, the vaccination offers the greatest benefits to the local population by reducing the time peak arrival and infected population. The policy scenario of these results can be implemented that the lower the population of vaccinated can be used to control the exposed and infected population in flattening the curves.

Author Contributions:

Conceptualization and methodology; MSDW, NUR, SPJ, IG, PCW; Software; SPJ; Formal analysis; SPJ and NUR; Original draft preparation; NUR; Writing; NUR, IG, PCW; Review, editing and supervision; MSDW, NUR, SPJ. All authors have read and agreed to the manuscript.

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TABLES

Table 1. Disease characteristics

Parameter	Modelled value	Reference
Basic reproductive number (R_0)	2, 4, 6	Assumed
Latent period prior to infectivity	3.2 days	[15]
Duration of infectivity	8.5 days	[1, 9]
Time from infection to death	22 days	[16]
Infection Fatality Ratio (IFR)	0.66%	[3, 16]

Table 2: Model parameters

Parameter	Definition	Value	Reference
N	Total Estimated Population	21,919,000	[17]
S	Susceptible 'Individuals in the population who do not infected, vaccinated or immune'	21,919,000–1=21,918,999 (on day 1 - 11.03.2020)	Assumed
E	Exposed 'Individuals exposed but not yet infectious'	1 (on day 1)	Assumed
I	Infected 'Individuals able to transmit infection'	0 (on day 1)	Assumed
R	Recovered 'Individuals neither infectious nor able to be infected'	0 (on day 1)	Assumed
V	Vaccinated 'Vaccinated individuals who have not yet achieved protective immunity'	0 (on day 1)	
R_0	Basic reproduction number 'New infections generated by each infectious individual in a susceptible population without transmission reduction measures'	2.53	[15]

α	Abrogation of infectivity as the susceptible fraction falls	1.2[a]	[18, 19]
β	Transmission coefficient ($R_t.\gamma$)	Derived	
γ-1	Infectious period 'Time from the onset of infectiousness to reversion to non-infectiousness'	8.5 days	[1, 9]
δ	Vaccination rate 'Proportion of the *Susceptible* population undergoing vaccination each day'	0.06%	[3]
ε	Vaccine efficacy 'Relative risk reduction of infection achieved through vaccination'	40%, 60%, 80%	Assumed
η-1	Latent period 'Time from exposure to the development of infectiousness'	3.2 days	[15]
ς-1	Time to develop protective immunity after vaccination	2 to 3 weeks	Assumed
IFR	Infection fatality ratio 'Proportion of all infections that result in death'	0.66%	[16, 20]

[a] *Recalibrated to match the final population incidence of an unmitigated epidemic given R_0 = 2.4 reported in the individual-based microsimulation model by Ferguson and others (Ferguson, et al., 2020), when applying the parameters used in Moss and others (Moss et al, 2020).*

Table 3: Relationship between different vaccination coverages with the infected population 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

FIGURES

Figure 1: SEIRV Model with Transition Forces

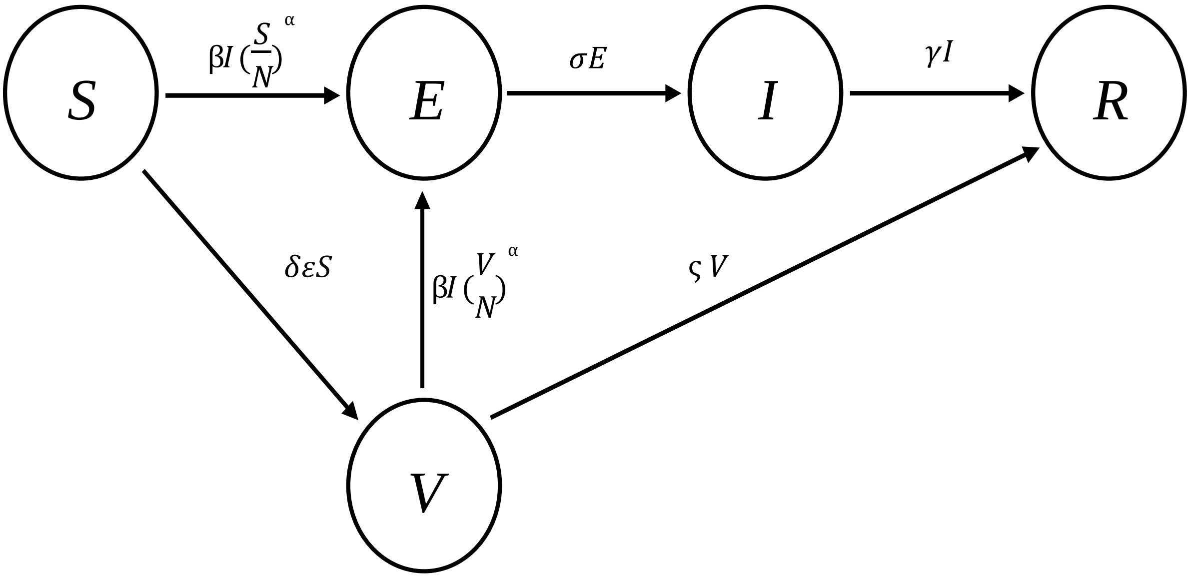


Figure 2: Evolution of infectious proportion without vaccination with different R_0 values

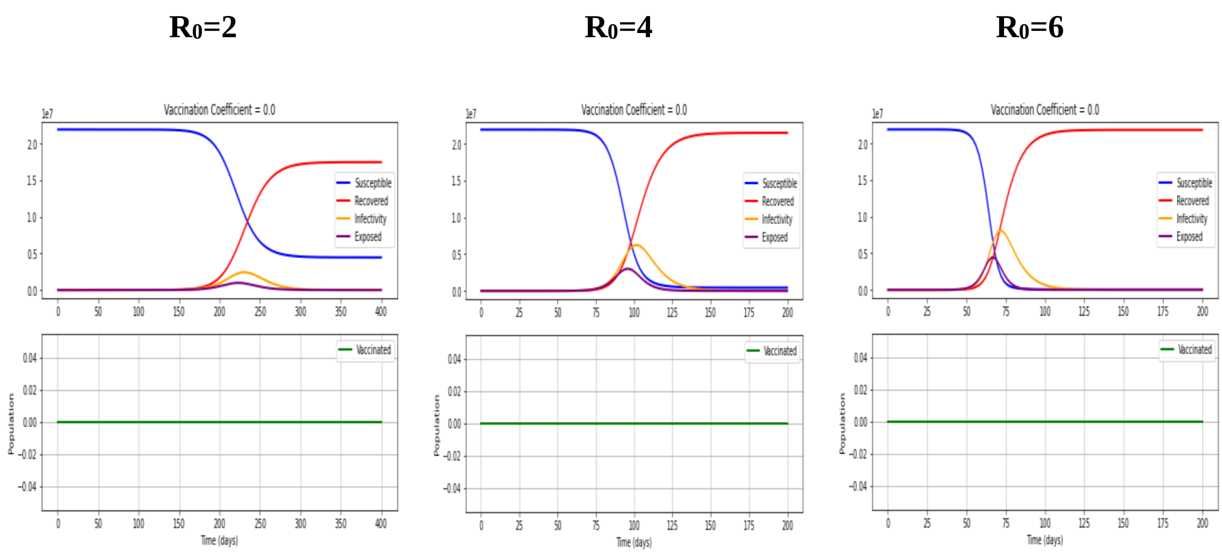


Figure 3: Evolution of infectious proportion under different levels of vaccination coverage

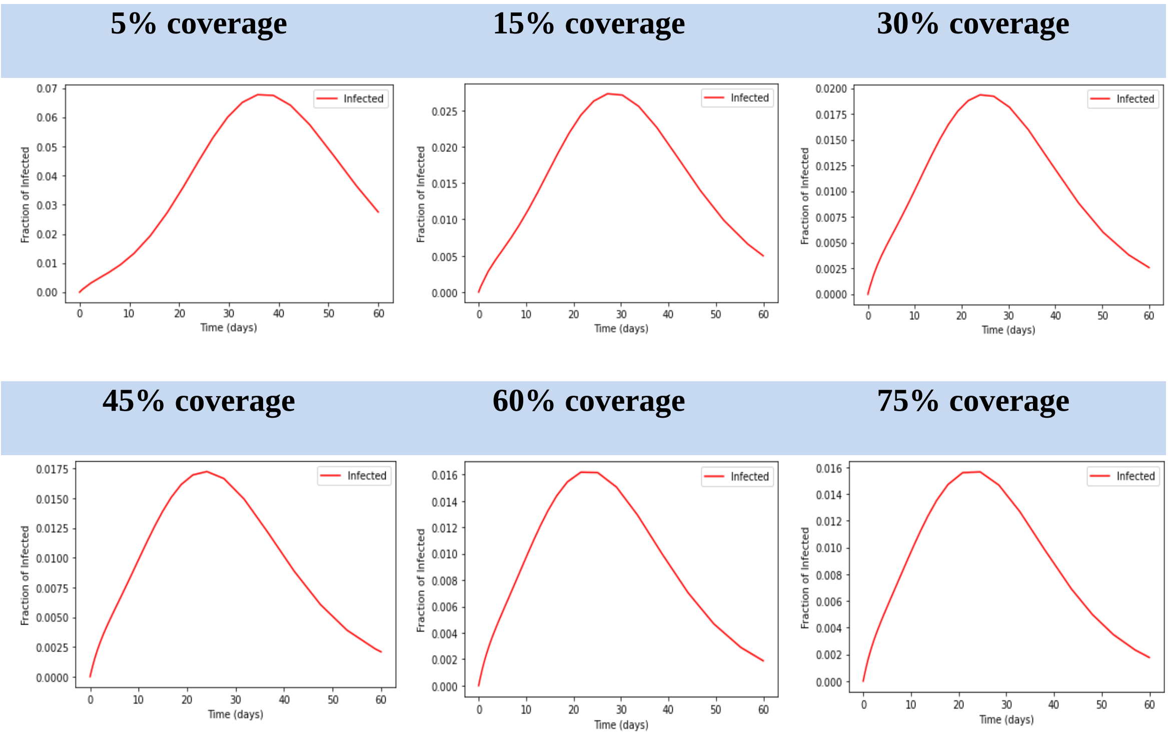


Figure 4: Prediction based on the SEIRV Model considering the parameter R_0 and Vaccine efficacy variation (Vaccine efficacy=40%,60%,80% and R_0=2,4,6)

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

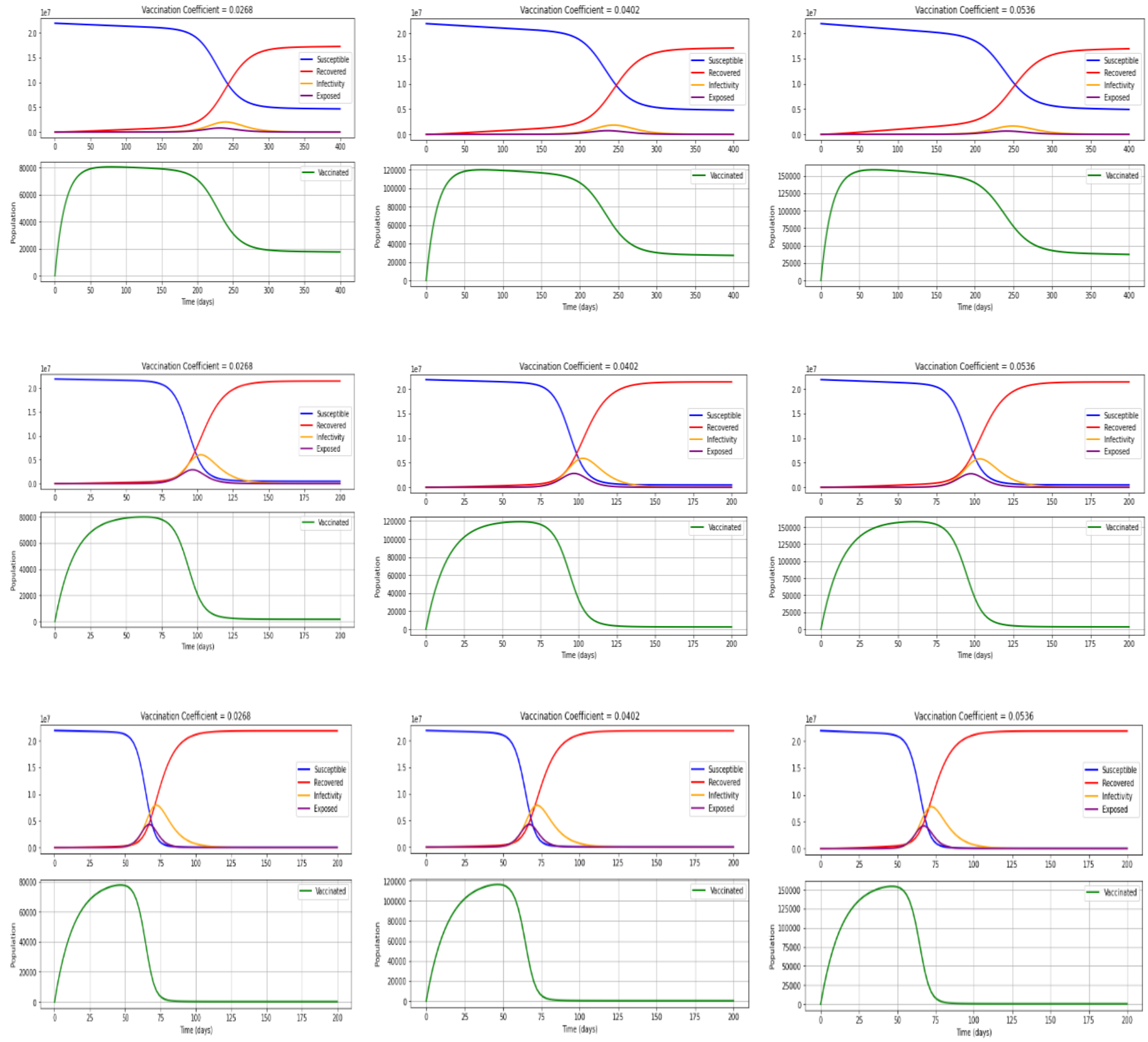


Figure 5: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), Vaccine efficacies (40%, 60%, 80%) and R_0 of 2, 4 and 6

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

R_0 **Vaccination rate (per day)**

1% **2%** **5%**

2

4

6

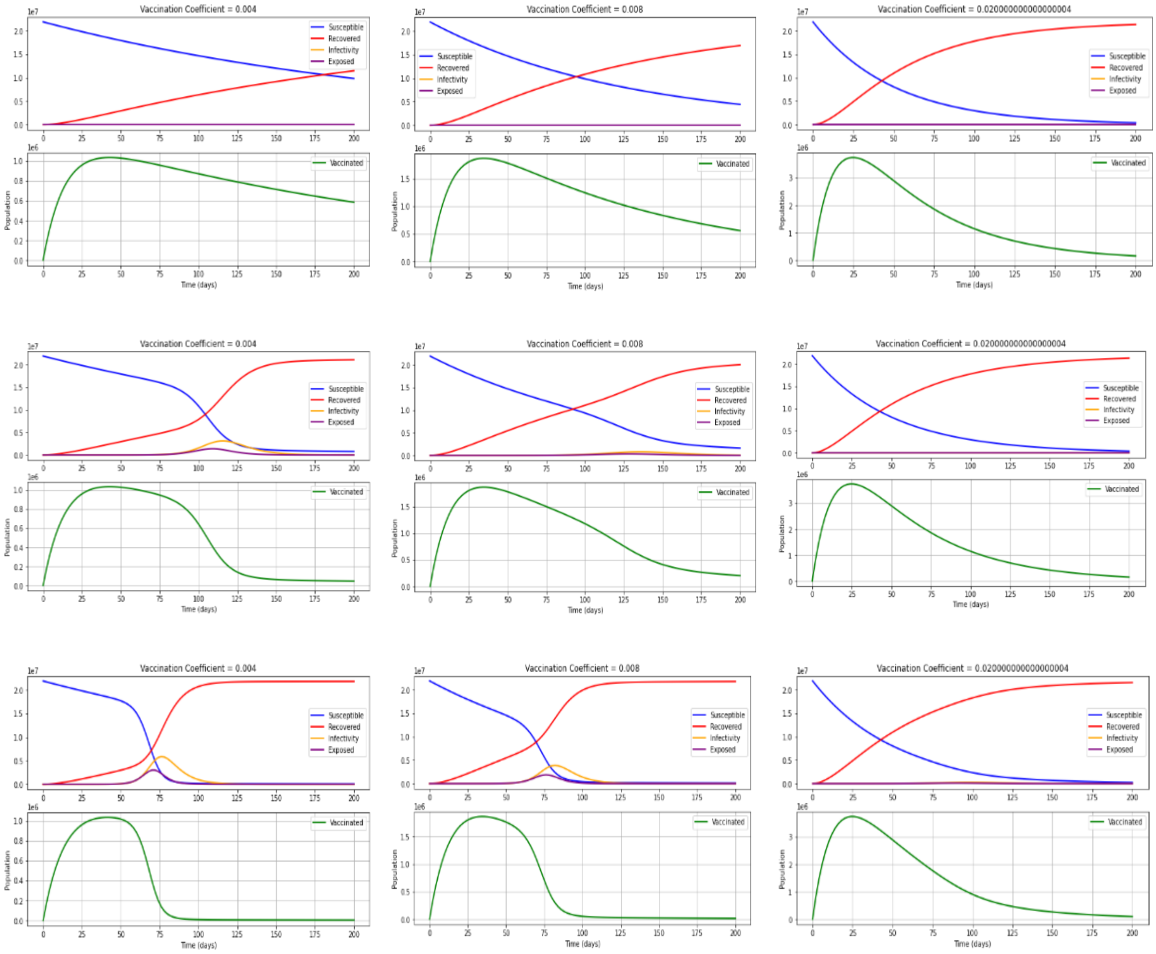
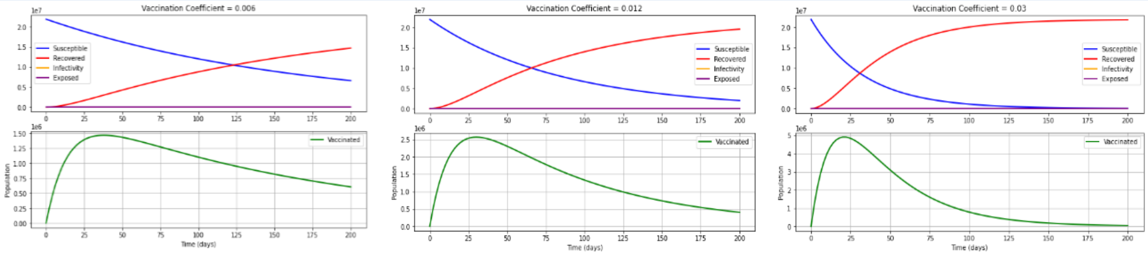


Figure 5b: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), R_0 of 2, 4, 6 with 60% Vaccine efficacy

R_0	Vaccination rate (per day)		
	1%	2%	5%

2



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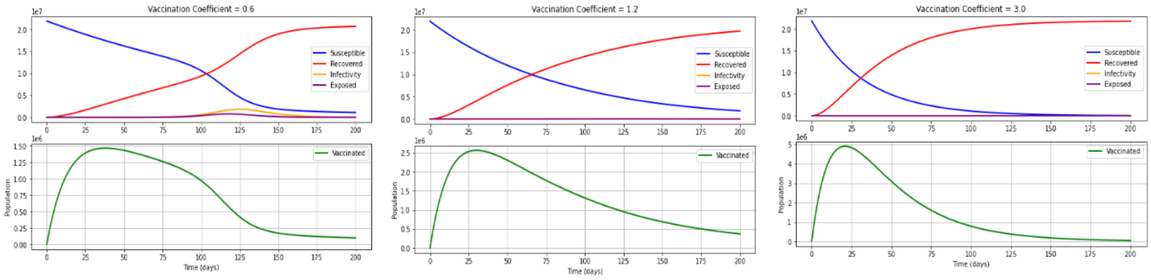

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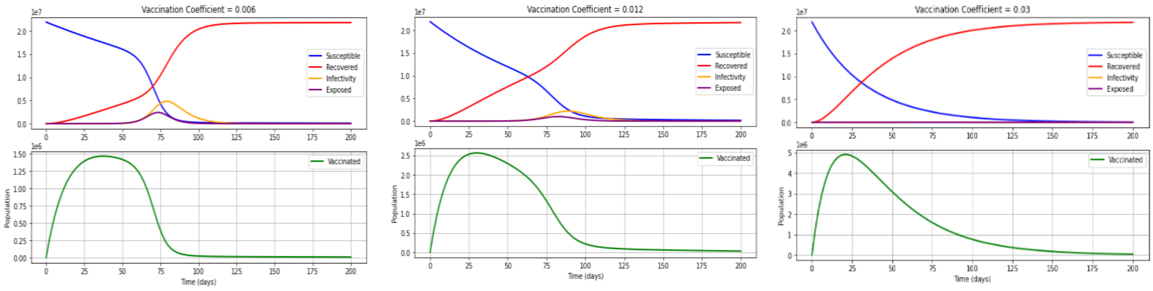
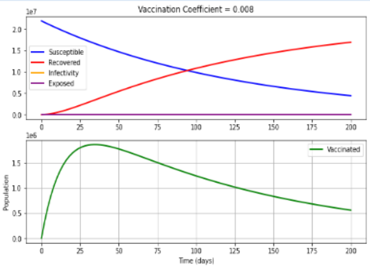
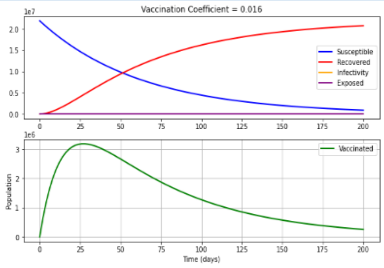
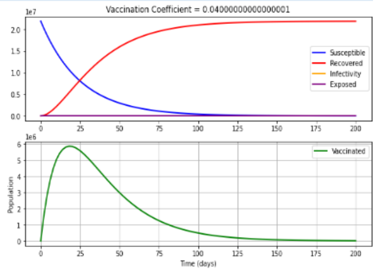
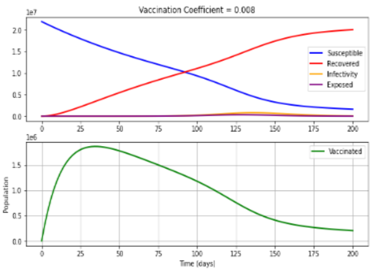
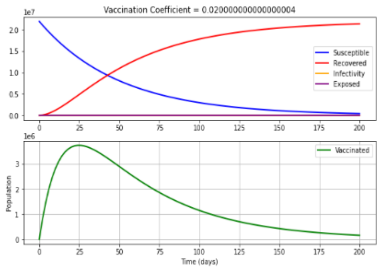
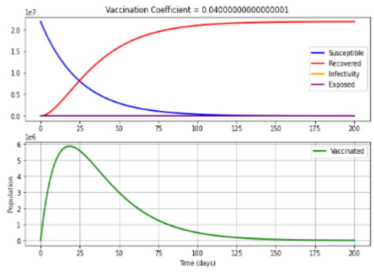


Figure 5c: Evolution of SEIRV under different levels of Vaccination rates (1%, 2%, 5%), R_0 of 2, 4, 6 with 80% Vaccine efficacy

R_0	Vaccination rate (per day)		
	1%	2%	5%
2			
4			
6