

# Monitor the Progression of Covid-19 Post Lockdown Using Mathematical Models

## Abstract:

The ongoing pandemic, corona disease (Covid-2019) has put Mathematical models in the spotlight. During pandemics, there is a critical need to understand both the likely number of infections and their time course to inform both public health and health care systems responses. A common approach is to use epidemic compartmental models, such as the *Susceptible-Infected-Removed* (SIR) model. This model is popular because of its simplicity, which allows Mathematical modelers to approximate disease behavior by estimating a small number of parameters. In India, country wide lockdown was imposed on 24<sup>th</sup> March to contain the spread of the disease and the phased reopening started after 75 days i.e. from 8<sup>th</sup> June and now we are just following the basic guidelines. Here, the SIR model is used to predict and monitor the progression of the corona disease post lockdown. The model parameters like basic reproduction number  $R_0$ , transmission rate  $\beta$ , recovery rate  $\gamma$  are reported at state level.

**Keywords:** Basic Reproduction Number, Transmission Rate, Recovery Rate, Epidemiological model

## 1. Introduction:

The World Health Organization (WHO) declared the outbreak of the novel coronavirus, COVID-19, as a pandemic on 11<sup>th</sup> March 2020. Viruses have varying abilities to infect people. COVID-19 is more infectious than other coronaviruses such as SARS or MERS-CoV with the “case fatality rate” (CFR) or risk of dying from the new coronavirus is about 4.4% (although this risk varies by geography and can change over the course of a pandemic).. India is not an exception to this, and the Indian prime minister Narendra Modi announced an unprecedented three-weeks nationwide lockdown on the 24<sup>th</sup> March 2020 and got extended till 31st May. After 75 days of strict lockdown phase, reopening started in India from 8<sup>th</sup> June.

An important variable in many epidemic models is the number of individuals that are infected at a given time. However, in a real epidemic scenario, only the number of infected individuals that have been detected as “positive” is available, while the actual number of infected people remains unknown. A common assumption made in the literature is that the observed cases are the actual ones. Clearly, this assumption is unrealistic and may lead to wrong epidemiological interpretations/conclusions. Here, we studied the post lockdown scenarios and monitored the spread of the disease across the country and the necessary parameters of the Time Series & SIR model have been estimated across all states of India. So that we identify which states require more attention.

## 2. Data

In this paper we will working with the following datasets –

- <https://www.kaggle.com/sudalairajkumar/covid19-in-india>

## 3. Methodology

Legendary statistician Prof George Box, once said -

***“All models are wrong, but some are useful”.***

Keeping this in our mind, here in this paper, we take a model agnostic two-prong approach. One is to understand the severity of the ground situation; and the second is the prediction, which will help the health officials to make the plans accordingly. The epidemic models for infectious disease yield insights into the dynamic behavior of the disease spread. With new insights, health officials can develop more effective disease intervention strategies. Besides, such epidemic models are also used to forecast the course of the epidemic.

### 3.1 SIR Epidemiological Model

The popular epidemic model for an infectious disease is the Susceptible, Infected, Recovered (SIR) model. The model considers a closed population. To start with, a few infected people are added to the population. It assumes that the mixing pattern is homogeneous. During the period of the sickness, the contagious people each infect on average  $R_0$  other people, who each then go on to infect  $R_0$  others, who are susceptible. The  $R_0$  is popularly known as the Basic Reproduction Number. The  $R_0$  is the fundamental quantity of the disease progression, and higher  $R_0$  means more people will tend to be infected in the course of the epidemic. The major advantage of the SIR model is it gives a number  $R_0$ , which can be used to benchmark and compare the ground situation of different states and resource allocations can be made to those states which are hard hit. The SIR model can be described as,

$$\begin{aligned}\frac{ds}{dt} &= -\beta \frac{SI}{N} \\ \frac{dI}{dt} &= +\beta \frac{SI}{N} - \gamma I \\ \frac{dR}{dt} &= +\gamma I\end{aligned}\tag{1}$$

where S, I, and R are the number of people in the population that are susceptible, infected and recovered. The  $\beta$  is the transmission rate. Each susceptible person contacts  $\beta$  people per day; a fraction  $\frac{I}{N}$  of which are infectious.

Therefore  $\beta \frac{SI}{N}$  move out of the susceptible group and go into the infected group. The transmission rate is the average rate of contacts a susceptible person makes that is sufficient to transmit the infection. The parameter  $\gamma$  is the recovery rate, and  $\gamma I$  is the flow out of the infected crowd and goes into the recovered group. The average duration a person spends in the infected group is  $\frac{1}{\gamma}$  days. In this paper, we follow the SIR implementation methodology .

Given  $R_0$ ,  $\beta$  and  $\gamma$ , the implementation of the SIR model is straightforward via the Scipy integrate package using function ODEINT, a solver for initial value problems of differential equations, see [1]. It is known that  $R_0 = \frac{\beta}{\gamma}$ , see [4]. However, we need some good estimates of the  $R_0$ , so that we can implement the SIR model and predict the disease progression in India. In order to estimate the  $R_0$ , we calculate the all possible  $\beta$  and  $\gamma$  values with respective to each day using the dataset(2) and differential equations(1), calculated  $\beta$  and  $\gamma$  values will be distributed and visualized by Box plot in order get the Interquartile Range of  $\beta$  and  $\gamma$ . With the help of Interquartile Range of  $\beta$  and  $\gamma$  values, we calculate the Susceptible, Infected and Recovered using ODEINT function looping  $\beta$  values over each  $\gamma$  value. Then we calculate the Mean Square Error (MSE) in the following way:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where  $\hat{y}(n)$  is the new incidence estimated from the SIR model described in (1) at time point t, and  $y(n)$  is the actual incidence observed in the data at time point t. With help of MSE, we calculate the Infected and Recovered MSE values and estimate the  $\beta$  and  $\gamma$  for which the MSE is minimum. With estimated  $\beta$  and  $\gamma$  values, we calculate the original Susceptible, Infected and Recovered values using ODEINT function and monitor the disease progression of the post lockdown and calculate the  $R_0$  values to top most infected states in India.

### 3.2 Model Training Strategy for India to monitor the spread of the disease post lockdown

We use the Regression model to estimate  $\beta$  and  $\gamma$  values by calculating the minimum MSE values for Infected and Recovered and perform hyper parameter tuning to come across the various scenarios and estimate the Susceptible, Infected and Recovered.

## 4. Analysis and Prediction

Exploratory Data Analysis (EDA) is important to develop good predictive models.

Maharashtra's number of cases are almost double that of Karnataka, Andhra Pradesh and Tamil Nadu. One of the reasons for this is there are few highly populous cities like Mumbai, Pune and Nagpur which account for 21% population of Maharashtra. Then there are these important metro cities like Chennai, Bangalore, Kolkata, Delhi, Jaipur, Hyderabad etc which are very famous for tourist attractions as well as in general public as big cities. An account of those, we can see Karnataka, Tamil Nadu, Delhi and West Bengal in top 10 contributors. Another point is, if we observe in (figure 1 below), the green and blue points for Andhra Pradesh, Tamil Nadu and Odisha are almost overlapping which suggests that most of the cases in these states we cured.

The population density of India is 382/sq.km which is counted in one of the highest values when compared to 93 in USA, 153 in China, 270 in UK and 9 in Russia. That means, there are on average 382 people per kilometer in India and when we compare the population of the North Eastern states which are very meagre, the other states get much more densely populated. This is one of the prime reasons for such a big boost in the number of cases.

Looking at the comparison of lines (figure 2 below), the number of deaths till May-June are almost negligible when compared to the actual number of cases which have come out later.

Though the number of cases increased very much, the death rate is very impressively almost zero (figure 3 below). That means the lockdown if followed would have very greatly reduced the number of cases we got later on. In the post lockdown phase, the death rate and confirmed cases increased swiftly as people were roaming freely outside.

Looking at the bar chart (figure 4 below) comparison between the total number of samples and the number of positive cases, it is clear that there were far too many samples collected and the positivity ratio is very less. This means that there were many people who were showing symptoms because of climate change or some other reasons and not covid. Also, since our government was also testing all the family members of any covid patient, it is good to see the difference of ratios.

#### **Time-Series Model:**

##### **Prediction of Disease Progression for India using Time Series model -**

We have done the future predictions for the top 5 states using ARIMA models and have analyzed the residual plots to test the model performance. We have predicted the cases for 15 days and observed that for almost all the states it shows a decreasing trend except Kerala where it shows an increasing trend. Performed the log transformations on the series to make it stationary

#### **SIR Model:**

**State wise  $\beta$ ,  $\gamma$  and  $R_0$  :** In Table (1), we present the state wise  $\beta$ ,  $\gamma$  and Basic Reproduction Number,  $R_0$ , as of 09 December, 2020 for the top most infected states in India. we see the  $R_0$  for Maharashtra ( $3.931577e-10$ ,  $0.017066$ ,  $2.30374838860893e-08$ ), Andhra Pradesh( $6.583312e-10$ ,  $0.023043$ ,  $2.8569682767000822e-08$ ), Tamil Nadu ( $6.595573e-10$ ,  $0.021765$ ,  $3.030357454628992e-08$ ), Karnataka( $9.146740e-10$ ,  $0.024165$ ,  $9.690432059312285e-08$ ) and Delhi( $1.516165e-09$ ,  $0.015646$ ,  $3.785118973722326e-08$ ). With the help of estimated  **$\beta$ ,  $\gamma$  and  $R_0$** , we could predict the future progression of COVID-19 using the SIR model.

## **5. Discussion**

Here we present a point by point discussion of our analysis and prediction. With estimated  **$\beta$  and  $\gamma$**  for each state in India, We could predict the future COVID-19 disease progression in the top most infected states in India. We are able to predict the number of Infected and Recovered cases on a particular day using the SIR model with estimated  $\beta$  and  $\gamma$ . In Figure 5 (below), the plot shows the future prediction of COVID-19.

#### **References:**

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## Tables and Figures

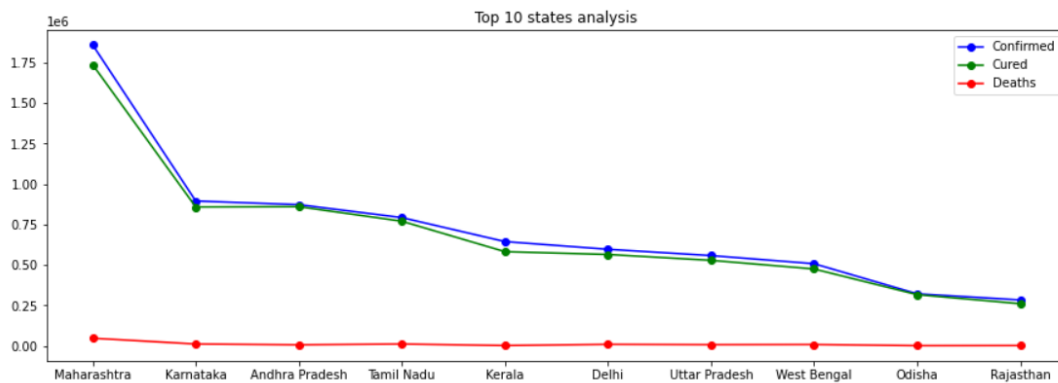


Figure – 1

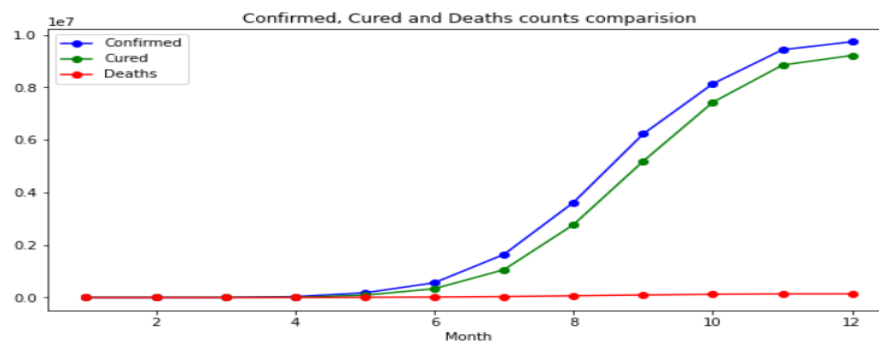


Figure – 2

Covid India Analysis

Total Testing v/s Positive

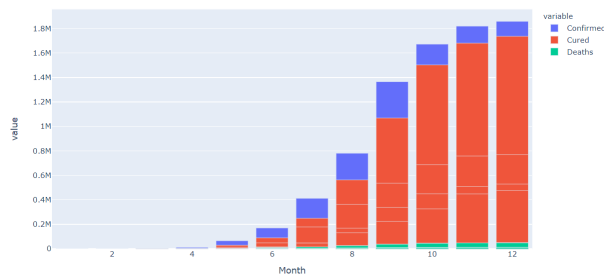


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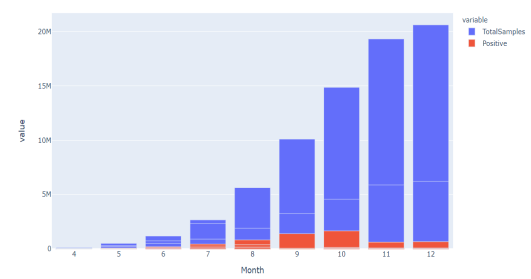
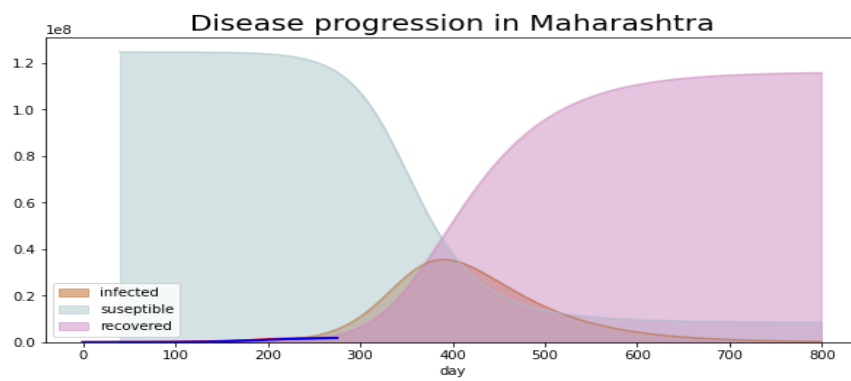


Figure – 4

State	$\beta$	$\gamma$	R0
Maharashtra	3.931577e-10	0.017066	2.30374838860893e-08
Andhra Pradesh	6.583312e-10	0.023043	2.8569682767000822e-08
Tamil Nadu	6.595573e-10	0.021765	3.030357454628992e-08
Karnataka	9.146740e-10	0.024165	9.690432059312285e-08
Delhi	1.516165e-09	0.015646	3.785118973722326e-08

Table - 1



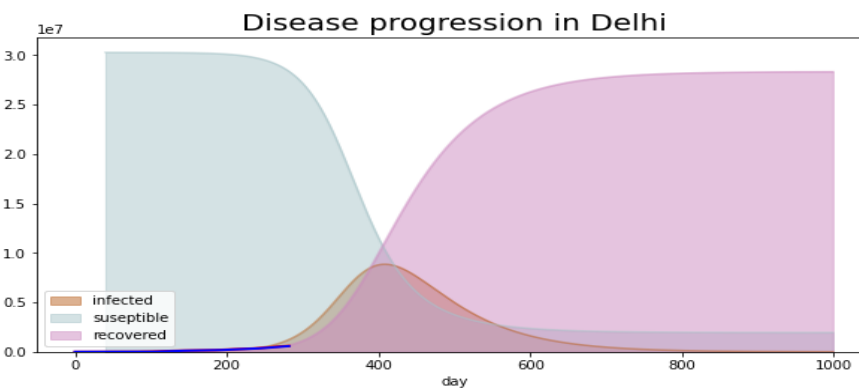
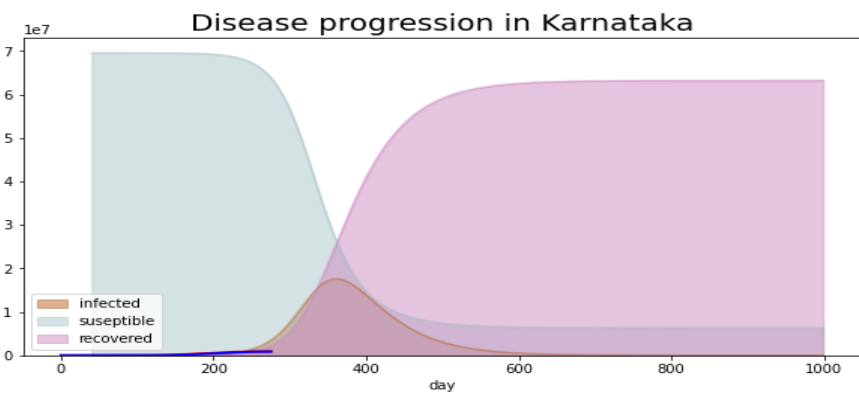
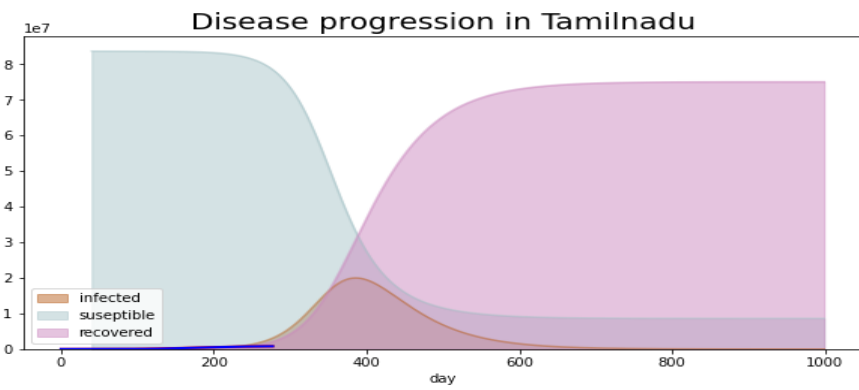
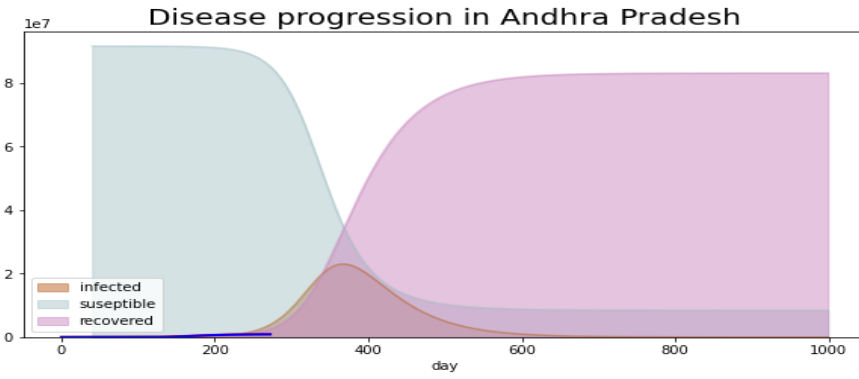


Figure – 5

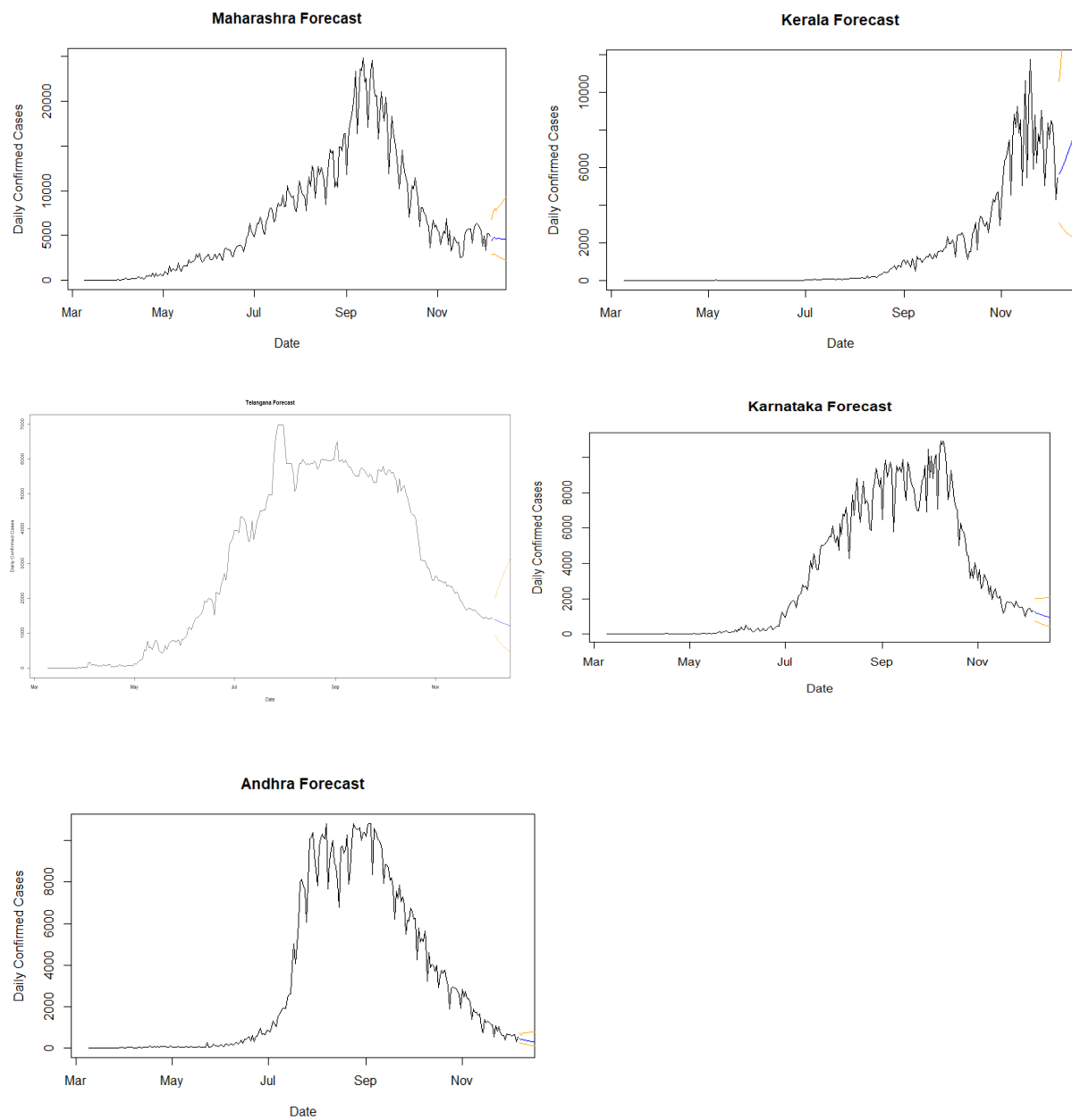


Figure – 6