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TECHNICAL NOTE

Analysis of Second Wave of COVID-19 in Different Countries

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Abstract
We analyse the evolution of the second wave of the COVID-19 pandemic in several countries by using a logistic model. The model uses a regression analysis based on the least-squares fitting. In particular, the growth rate of the infection has been fitted as an exponential increase, as compared to a power law increase, reported previously in logistic models. The data shows that the increase in the exponent of the exponential increase is around 0.03 day^{-1}, with a standard deviation of 0.01 day^{-1}. The present results suggest that duration of the peaking of the second wave is almost same for several countries considered. The growth rate is also on the same order of several countries regardless of the total number of infections in a particular country. Since the decay of the growth rate is self-similar to that during the increase in the second wave of several countries, we can predict the end of the second wave in India. The model suggests that the second wave will end in the first week of August 2021, with a growth rate of 0.1% day^{-1} at that time.

Keywords COVID-19 · Second wave · Epidemiology · Logistic model

Introduction

The COVID-19 pandemic is one of the worst humanitarian crisis that mankind is facing in at least a century. During April-May 2021, India has witnessed a deadly second wave, while most other countries have gone past the second peak, with some countries even experiencing third and fourth waves. It will be useful to know the start point, intensity and duration of these waves beforehand, as that would help the people and the governments plan better and utilize the available resources with them to manage the pandemic well. The current study, conducted in the context of the ongoing second wave in India, examines the ascending phase of the second wave. Certain similarities in the trend are noted when the data for India is compared with other countries.

Several efforts have been made to curve fit the data separately in the different phases (i.e., growth and decay of different waves) of the pandemic. For example, Verma et al. (2020) focused on the initial growth of the pandemic and showed the existence of power law regimes between the initial exponential growth and flattening of the curve. The power law regime could be well described by quadratic, linear, square-root functions for several countries considered in their analysis. Sharma and Nigam (2020) considered the increase in the number of infections in India for the initial four months. They found that the data can be fitted successively by exponential, quadratic, linear, quadratic, 4th-order polynomial functions. Bhardwaj (2020) used a logistic model with an exponential function (instead of a linear function) fitting the growth rate in the initial period after peaking of infections for various countries. The analysis of Verma et al. (2020) was later extended to various Indian states by Asad et al. (2020). Anand et al. (2020) used an augmented SIR model to predict the infections in the Indian state of Kerala during the early phase of the pandemic. Mandal et al. (2020) proposed a novel model considering Susceptible, Exposed, Hospitalized infected, Quarantine, and Recovered or Removed classes. They used their model to forecast the number of cases in three Indian states, namely, Maharashtra, Delhi, and Tamil Nadu. Other model results in the early phase of the pandemic for India are available in References Ansumali et al. (2020), Sarkar et al. (2020), Samui et al. (2020), Bhattacharjee et al. (2021), Dauji (2021).

Since the decay of the number of daily infections is slower than the growth, Ranjan (2020) considered skewed

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Gaussian function and piecewise linear functions to fit the decaying part of the curve. Sharma et al. (2021) suggested normalizing the data with the maximum time and maximum infection counts. They pointed out that the epidemic data for the first wave of eight nations normalized in this manner follow a universal curve. The predictions from their model was found to match well with the supermodel of the country (Ansumali et al. 2020).

It is evident that while a large amount of effort went in modelling the initial growth of the pandemic, there are not many studies modelling the entire number of cases seen till date in India. Further, the onset and rise of the second wave in India has not been modelled. Therefore, the present work focuses on the second wave, and compares the data for India with several other countries. The primary objective of this work is to learn from the data by comparing and contrasting the trends from various countries, which could help better understand and predict the subsequent waves. This may help policymakers to put mitigation measures in place in advance and appropriately allocate health resources at their disposal.

Logistic Model

The following ordinary differential equation governs the evolution of an infectious disease in a given human population (Bhardwaj 2020; Vattay 2020):

$$\frac{dN}{dt} = \lambda N \tag{1}$$

where N is number of people infected at a given time t and λ is the growth rate of the infections. The model uses reported field data of the infections of a population over a specific time period $[t_1, t_1, t_2, ...,t_P]$, say $[N_1, N_2, N_3, ...,N_p]$, where subscript 1 and p refers to the first and present day of the outbreak. The growth rate can be numerically approximated by a second order accurate central difference formula for the derivative in Eq. 1 and is given as follows (Bhardwaj 2020),

$$\lambda_{t_i} = \frac{N_{t_{i+1}} - N_{t_{i-1}}}{2\Delta t N_{t_i}} \tag{2}$$

Considering the unit of time as day and the data is available for each day, we obtain $\Delta t = 1$ day in the above equation. We estimate λ_{t_i} from the data of different countries given in public domain (https://coronavirus.jhu.edu 2021; https://www.worldometers.info/coronavirus 2021; https://www.covid19india.org 2021) and use a regression analysis based least-squares fitting to the data of λ_{t_i} for the second wave. In our previous work (Bhardwaj 2020), it was shown that the following form of the decay of the growth date fits well as compared to a linear fit for several countries:

$$\lambda = ae^{-bt} \tag{3}$$

where a and b are constants for a given time-series. In the present work, we assume the following form of the growth rate during the second wave:

$$\lambda = ae^{bt} \tag{4}$$

We show that this form works well for several countries, with the value of constant b is range of 0.03–0.04 day^{-1} for several countries, with a standard deviation of 0.01 day^{-1}. In addition, the number of future infections in the second wave in India has been predicted for $t > t_p$ assuming the decaying growth rate, as given by Eq. 3. Since the decay rate and the growth rate of infections in the second wave has been found almost the same for several countries, we predict the evolution of infections in India in the second wave. We predict the total and daily infections, as well as the time of the end of the second wave, which is declared if $\lambda_{t_i} \leq 0.001$ day^{-1}, i.e. the growth of cumulative infections reduce below 0.1% day^{-1}.

Results

First, we plot the results of fourteen countries, given in Table 1. The countries are chosen if there were significant infections during the second wave in that particular country. The data used in the model is from 22 January 2020 to 30 April 2021. Time = 1 day corresponds to 22 January 2020 in all figures.

Universality of growth rate of infections in several countries

Figures 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 present the number of daily infections and growth rate for the 14 countries identified in Table 1. Notice from the figures for growth rate that the change in sign for the slope of growth rate occurs much before the number of cases start exploding. For Belgium, the change in slope from negative to positive occurs at around 160 days, whereas the number of cases started exploding only from 225 days onwards. A similar "early warning" can be seen from growth rate data for France (150 days and 210 days respectively), Germany (170 days and 250 days), Italy (160 days and 250 days), Netherlands (165 days and 230 days) and UK (150 days and 210 days). However, such an early change in slope is not seen in the data for Brazil, India, Peru, Poland, South Africa and USA.

Table 1 Data of second wave of COVID-19 in different countries the time span used in the model to fit the growth rate is listed in the table

Country	Start	Peak	Fit parameter b	R^2 value	Remarks on evolution of second wave
Belgium	160	275	0.0413	0.89	Early warning
Brazil	270	330	0.013	0.35	Slow increase in growth rate
France	125	285	0.018	0.79	Early warning
Germany	145	285	0.034	0.89	Early warning
India	380	453	0.055	0.99	Sharp increase in growth rate
Italy	160	284	0.05	0.95	Early warning with sharp increase in growth rate
Netherlands	168	265	0.03	0.96	Early warning
Peru	300	450	0.008	0.29	Slow increase in growth rate
Poland	230	280	0.041	0.90	Moderate increase in growth rate
South Africa	290	352	0.032	0.87	Moderate increase in growth rate
Spain	135	220	0.031	0.51	Moderate increase in growth rate
Sweden	220	298	0.033	0.31	Moderate increase in growth rate
U.K.	170	260	0.047	0.89	Early warning
U.S.A.	142	172	0.019	0.74	Slow increase in growth rate

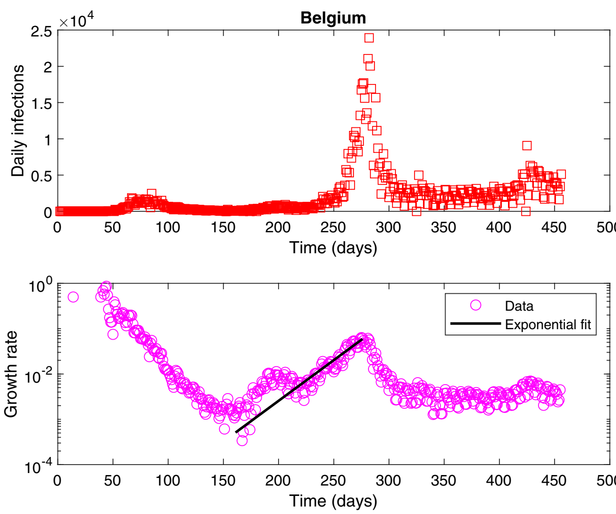

Fig. 1 Data for Belgium. Day 0 is 22 Jan, 2020 and data until 30 April 2021 is analysed. Time-history of daily infections (top frame), growth rate (bottom frame). In bottom frame, the data is shown by symbols while the solid lines are predicted from the model

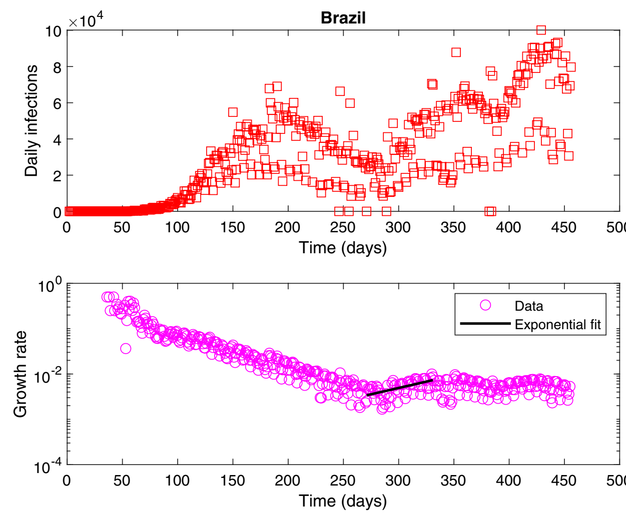

Fig. 2 Data for Brazil. Rest of caption is the same as of Fig. 1

The data therefore shows an early warning of 60–90 days for some countries, which, in hindsight, could have been useful in better managing the pandemic. The peak of the second wave also correlates with a change in sign for the slope of growth rate. Therefore, the growth rate is a good parameter to consider and plot. The data of daily infections of Brazil, Sweden and Peru show a lot of scatter and consequently, the fitted exponential fits of the growth rate show low value of R^2 (~ 0.30–0.35) as documented in Table 1.

For all the countries considered here (except Poland and USA), the growth rate for the second wave started at

$$\lambda = \frac{1}{N}\frac{dN}{dt} \sim 0.001\ day^{-1} \tag{5}$$

That is, the rate of new infections is about 0.1% of the baseline infections at the beginning of the second wave. However, the growth rate increases to different levels for different countries over their respective second wave. The maximum value for growth rate during the second wave is 10% (Belgium, France, Italy, Sweden) and only slightly lower for Germany, Netherlands, UK. Fig. 5 shows that the growth rate in case of India has plateaued at around 2% in the first week of May, with the maximum number of daily infections at around 0.4 million. After a few days, we should be able to see the end of second wave in India more distinctly with the model we have, since the growth rate is expected to go down exponentially after the number of daily infections start dropping. We discuss this aspect in the next section.

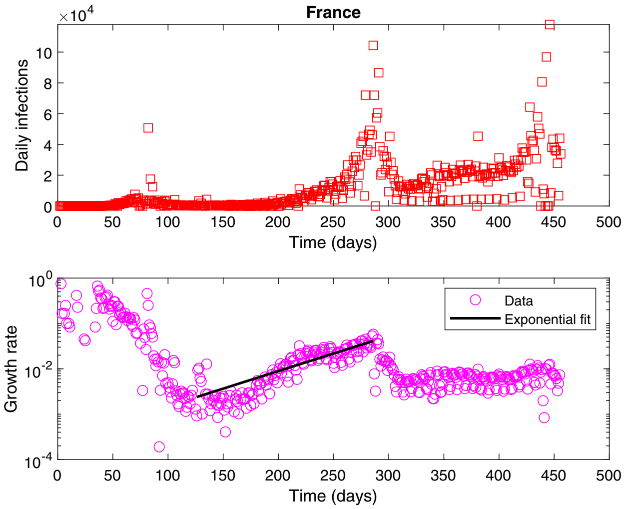

Fig. 3 Data for France. Rest of caption is the same as of Fig. 1

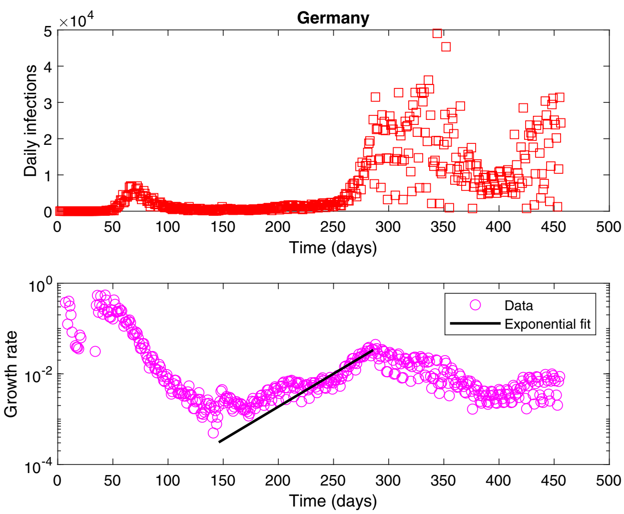

Fig. 4 Data for Germany. Rest of caption is the same as of Fig. 1

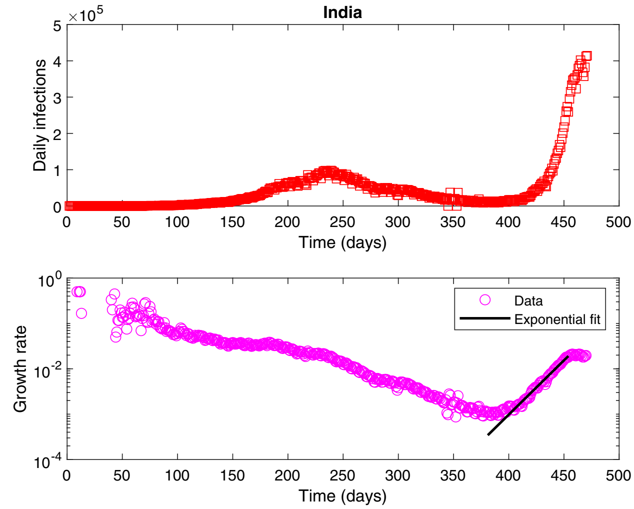

Fig. 5 Data for India. Rest of caption is the same as of Fig. 1

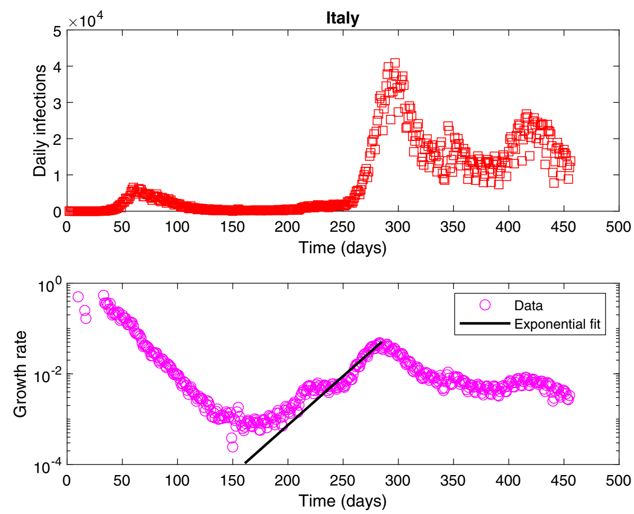

Fig. 6 Data for Italy. Rest of caption is the same as of Fig. 1

Prediction of end of second wave in India

The growth rate (λ) of second wave in several countries shows a remarkable feature. The slopes of λ in $\log(\lambda) - t$ plane for increasing and decaying λ are almost supplementary. Examples include, Belgium, Italy, Netherlands, Poland, South Africa, U.K. and U.S.A. *Assuming* that this feature would be true for the case of India, we predict the end of second wave in India.

If $\lambda = ae^{bt}$ for the increasing λ, we consider $\lambda = ce^{-bt}$ for the decreasing phase of the second wave. As seen in Fig. 5a, the peak of the second wave has arrived at around 471 day or around 7 May, 2021. Using the supplementary slope as found for the increase of λ, $b = 0.055$ day^{-1} and considering the growth rate will decay after 7 May, 2021, we obtain $\lambda = ce^{-0.055t}$, where t is the time on or after 7 May, 2021. We use the peak growth rate of 0.02 at $t = 0$ to obtain the coefficient, $c = 0.02$. Using this growth rate, the predicted trends for the growth rate, daily infections and cumulative infections are plotted in Fig. 15a–c, respectively. The end of second wave will occur *say* at $\lambda = 0.1\%$ day^{-1}, which corresponds to 566 day or 10 August, 2021. The daily and cumulative infections will be around 3000 and 30 million, respectively, at that time. Lastly, Fig. 16 shows comparison between model predictions and data obtained on 11 June 2021 for India. The predictions are in very good agreement for the growth

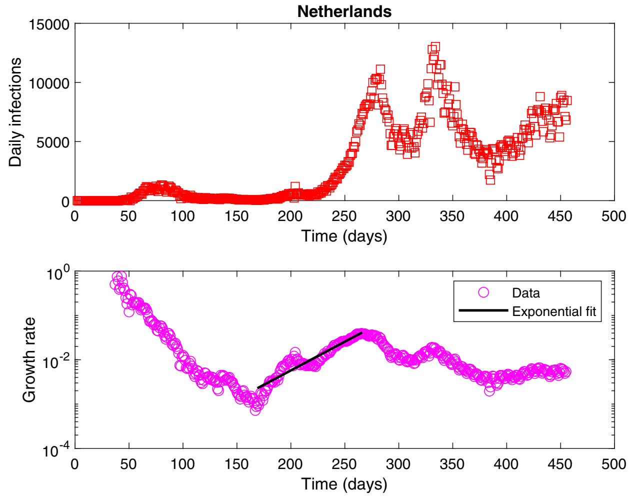

Fig. 7 Data for Netherlands. Rest of caption is the same as of Fig. 1

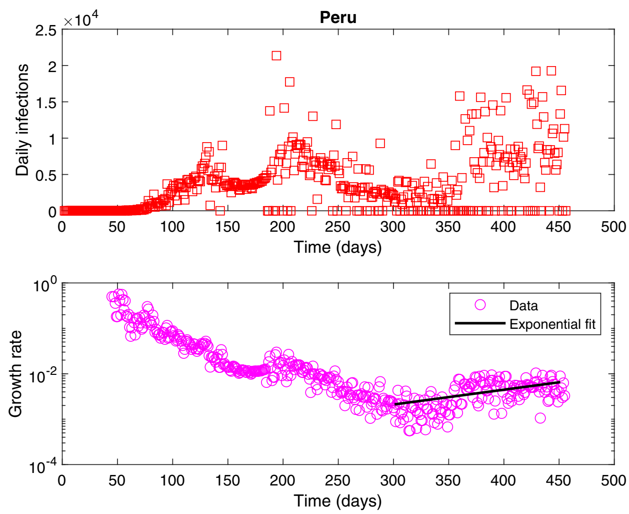

Fig. 8 Data for Peru. Rest of caption is the same as of Fig. 1

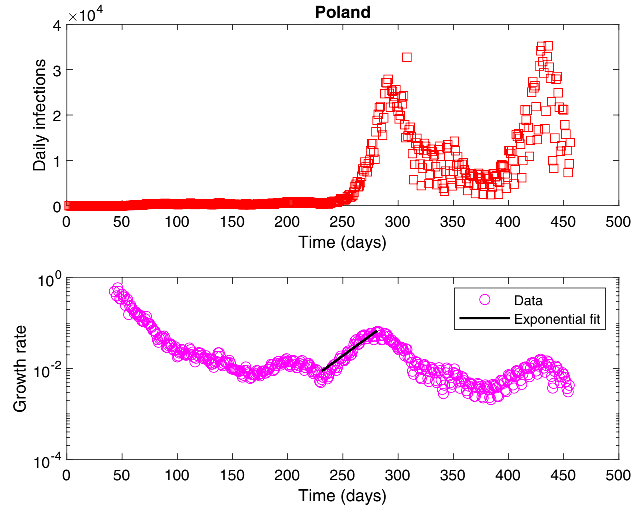

Fig. 9 Data for Poland. Rest of caption is the same as of Fig. 1

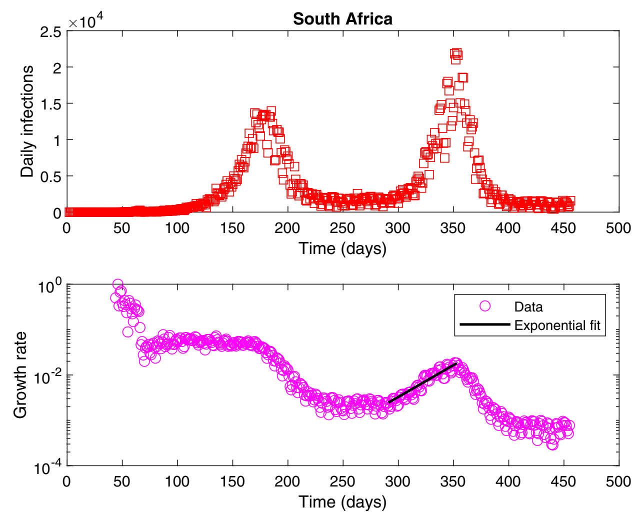

Fig. 10 Data for South Africa. Rest of caption is the same as of Fig. 1

rate, daily infections and cumulative infections, as on 11 June 2021.

Discussion

We have adopted a data driven approach in this work, as opposed to modeling the number of suspected, infected and removed cases done in SIR and other complex models. Our model therefore does not take into account the effect of quarantine, lockdown and other government measures taken to control the pandemic. The advantages of data driven approach has been recognized by several past researchers. For example, Ranjan (2020) emphasized the advantages of data driven approach given the non-uniform distribution of infections in different parts of a country, brought about, for example, by following different policies in different states of a country.

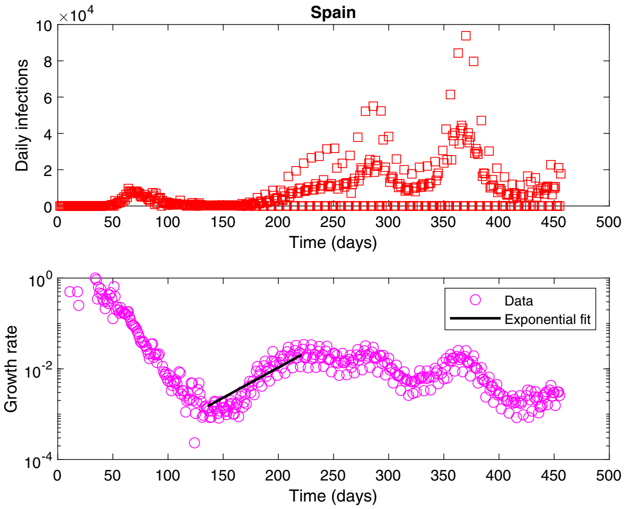

Fig. 11 Data for Spain. Rest of caption is the same as of Fig. 1

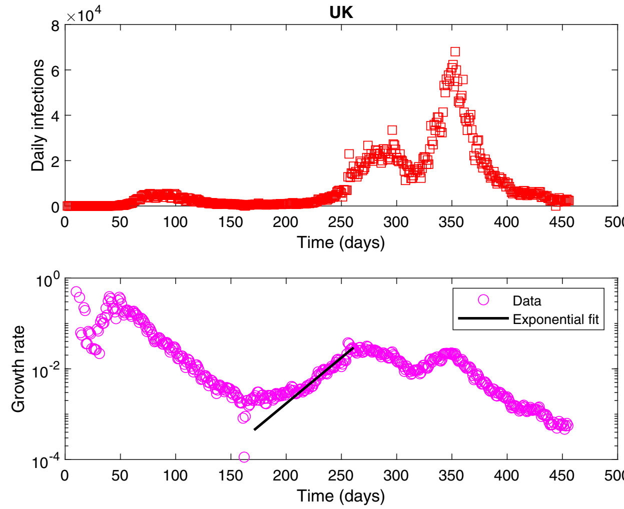

Fig. 13 Data for UK. Rest of caption is the same as of Fig. 1

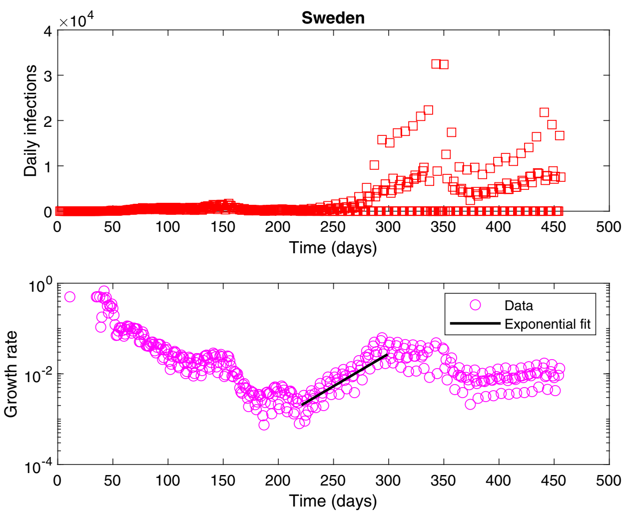

Fig. 12 Data for Sweden. Rest of caption is the same as of Fig. 1

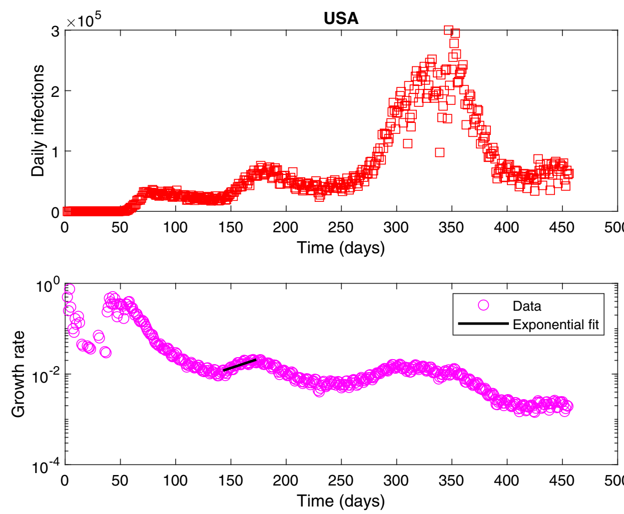

Fig. 14 Data for the USA. Rest of caption is the same as of Fig. 1

The data driven approach becomes further useful when an universal behaviour is seen from the data as in the present case. The same slope seen here for varies countries is perhaps not surprising. Sharma et al. (2021) also noted a similarity in data for several countries over a long period of time. The data of India has been predicted with reasonable fidelity using the present approach.

Conclusions

In summary, we have employed a logistic model to analyze the evolution of the second wave of COVID-19 pandemic. This predictive mathematical model uses a regression analysis based on least-squares fitting. Specifically, the growth rate of the infection in the second wave is found to be exponential of form ae^{bt}, as compared to a linear increase, for 14 countries. The exponent b is found to around 0.03 day^{-1}, with an standard deviation of 0.01 day^{-1}. Based on the self-similarity of the decay of the growth rate, we predict the end of the second wave in India by extrapolating the data available. The model predictions show that the

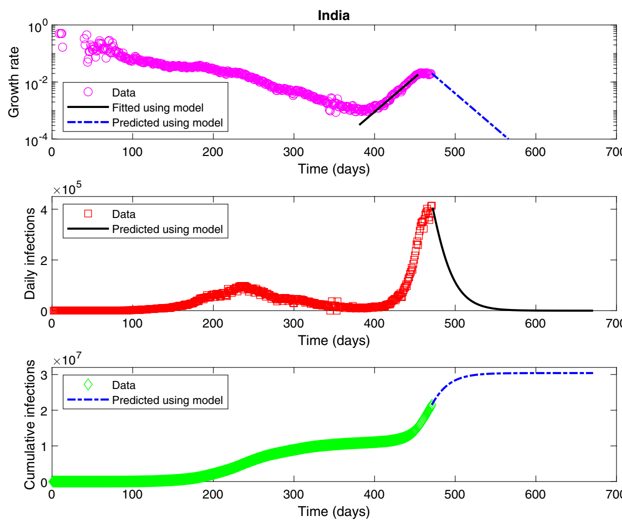

Fig. 15 Prediction for India. The end of the second wave is predicted at 566 day from the start of the pandemic or in first week of August. The growth rate will reduce to 0.1% in this week, according to the model predictions

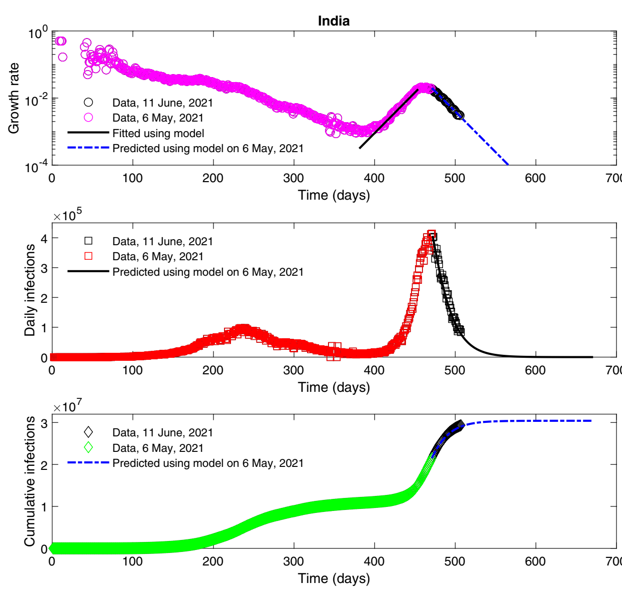

Fig. 16 Comparison of model prediction with data for India. The growth rate, daily infections and cumulative infections are in very good agreement with the data recorded after 6 May, 2021

the daily infections will be below 3000 in the first week of August 2021, with a growth rate of 0.1% day^{-1}.

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