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Short-term forecasts of COVID-19 spread across Indian states until 29 May 2020 under the worst-case scenario

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Abstract

The very first case of corona-virus illness was recorded on 30 January 2020, in India and the number of infected cases, including the death toll, continues to rise. In this paper, we present short-term forecasts of COVID-19 for 28 Indian states and five union territories using real-time data from 30 January to 20 May 2020. Applying Holt's second-order exponential smoothing method and autoregressive integrated moving average (ARIMA) model, we generated 10-day ahead forecasts of the likely number of infected cases and deaths in India until 29 May 2020. Our results show that the number of cumulative cases in India will rise to169109 [PI 95% (14426, 19455)], concurrently the number of deaths may increase to 4863 [PI 95% (4221, 5551)] by 29 May 2020. Further, we have marked the states (e.g. Delhi, Uttar Pradesh, Rajasthan, Madhya Pradesh, Maharashtra, Gujarat, and Tamil Nadu) where outburst is expected by considering the cases above three standard deviations. Under the worst-case scenario, Maharashtra is likely to be the most affected state with around 62628 [PI 95% (52840, 73555)] cumulative cases by 29 May 2020. However, Kerala and Karnataka are likely to remain in the lesser affected region. The presented results mark the states where lockdown by 1 June 2020, can be loosened.

Keywords: COVID-19; India; Prediction models; Statistics; Data; Indian states.

1 Introduction

COVID-19 illness, an on-going epidemic, started in Wuhan city, China, in December 2019 continues to cause infections in many countries around the world [1]. Considering the scale and speed of transmission of COVID-19, on 11 March 2020, the World Health Organization (WHO) declared it as a pandemic [2]. Thereafter, COVID-19 has become a threat to human life on the planet. It has shown rapid infections in almost all countries, and there is no cure available for this deadly virus. Presently governments have issued precautionary measures such as social distancing, sanitization of streets and markets, quarantine of suspected and infected cases, and lockdown of the communities at different scales (colonies, towns, states, and countries, etc.). In India, exponential growth has not been observed as compared to the USA and other European countries. It is due to the measures taken by the Indian government. It indicates that there is a strong influence of these measures, such as lockdown on the transmission behavior of COVID-19. On the other side, these measures create substantial economic losses to the communities, and hence actions mentioned above cannot be imposed for longer periods. Mainly, developing countries (such as India) cannot afford such payoff after some finite time. The Indian government has continuously reviewed every hour situation in every state. The government has become more focused on localizing the lockdown in particularly alarming states and few towns which are hotspots for COVID-19. For all these, it is important to have short-term forecasts which can be steering point for decision-makers and administrations. In this connection, data-based statistical models such as Autoregressive integrated moving average (ARIMA) and Holts method have shown effectiveness in predicting short-term forecast including the dengue fever [3, 4], the

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hemorrhagic fever with renal syndrome [5], Tuberculosis [6] and COVID-19 [7]. ARIMA has more ability compared to other prediction models like the support vector machine and wavelet neural network for drought forecasting [8]. Also, exponential smoothing methods have been widely used for forecasting of the population in West Java [9], an inflation rate of Zambia [10] including a prediction for epidemic mumps [11] and COVID-19 [12–17]. However, mainly, for India, the short-term forecast is not done thoroughly. As India has diversity across the states, it will be essential to study the spreading behavior of COVID-19 in different Indian states. This article presents a short-term forecast for various Indian states which are severely infected.

The main objective of the present paper is to present 10-day ahead forecasts from 21 to 29 May 2020 of the cumulative number of infected cases and deaths due to COVID-19. This work also presents the analysis of Indian states at the regional level to understand the spread of infection. The current situation of India is shown in Figure 1, with the cumulative number of infected cases and deaths from 30 January to 20 May 2020.

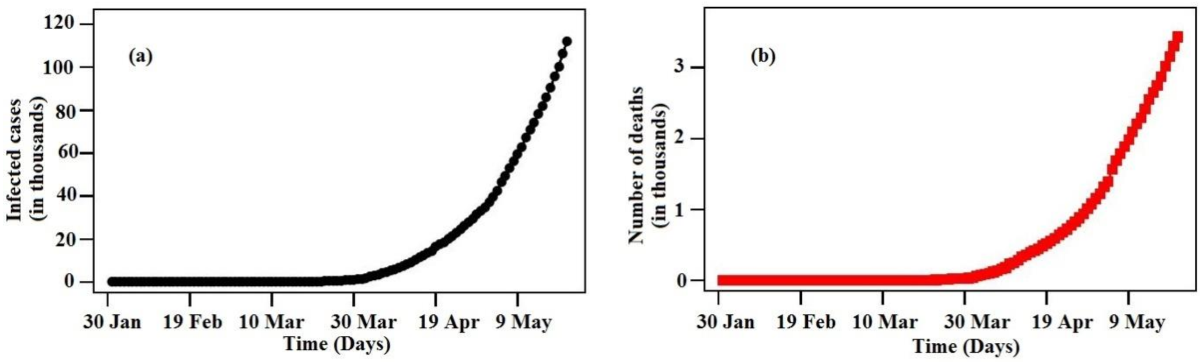

Figure 1: (a) Number of infected cases from 30 January to 20 May 2020; (b) Number of deaths from 30 January to 20 May 2020.

2 Materials and Methods

2.1ARIMAModel

The process whose statistical properties do not change with time, i.e. process with constant mean and constant variance, known as a stationary process, is a crucial collection of stochastic processes. Mathematically, the joint distribution of $X(t_1),...,X(t_k)$ and $X(t_{1+\tau}),...,X(t_{k+\tau})$ is the same for all $t_1,t_2,...,t_k$ of a stationary process. Simply put, shifting the origin of time by a quantity τ does not change the statistical properties of the process. Usually, dealing with real-time data, most time series does not exhibit stationarity in nature as they have no fixed mean. The properties of the crucial collection of models for which the d^{th} difference of the time series is a stationary mixed autoregressive moving average process (ARMA). These models are known as ARlMA models. The ARMA model, introduced by Box and Jenkins, is the collection of popular methods that are directly applicable to modeling and analyzing the time series [18]. The ARMA model is formed by the merger of two models, the autoregressive AR(p) model and the moving average MA(q) model. These models are directly applicable to time series with stationary behavior. In case the series is non-stationary, it must be dealt via differencing to make it stationary. Generally, the ARMA model after differencing is known as ARIMA (p, d,q). Addressing

$$H_t = \nabla^d X_t = (1-k)^d X_t \qquad (1)$$

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The general ARIMA model is given by

$$H_t = \alpha_1 H_{t-1} + \ldots + \alpha_p H_{t-p} + J_t + \ldots + \beta_q J_{t-q} \tag{2}$$

Hence, the ARIMA model can be written as

$$f(k) H_t = g(k) J_t \tag{3}$$

$$f(k) \nabla^d X_t = g(k) J_t \tag{4}$$

The expressions in the Eq. 4 are defined as: $f(k), g(k)$ are polynomials of degree *p, q* respectively *s.t.*

$$f(k) = 1 - \alpha_1 k - \ldots - \alpha_p k^p \tag{5}$$

and

$$g(k) = 1 + \beta_1 k + \ldots + \beta_q k^q \tag{6}$$

While, ∇^d is an operator, known as difference operator, and used to make the difference of time series stationary; and d is the difference value. In real-time data, taking the first difference (d=1) is usually found to be sufficient and occasionally second difference (d=2) would be enough to achieve stationarity.

Akaike Information Criterion (AIC) is one of the essential criteria to select between competing models. Mathematically,

$$\text{AIC} = \log\left(\frac{\sum_{t=1}^{T} e_t}{T}\right) + \frac{2p}{T} \tag{7}$$

The model which has the least AIC is selected as the best model. Autocorrelation functions (ACF) and partial autocorrelation functions (PACF) are used to select order of moving average process MA(q) and autoregressive process AR(p) respectively. In the process to investigate the stationarity of time series Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [19] and Augmented Dickey-Fuller (ADF) [20] tests are used. To reject the null hypothesis, the *p*-value must be smaller than the significance level.

2.2 Holt'sMethod

The numbers of confirmed cases and deaths in India are increasing day by day, as shown in Figure 1 thereupon the time series exhibit trend. Simple exponential smoothing methods should not apply in this case. When data shows the pattern, and there is no seasonality, Holt's method is a primary tool to handle it. Holt's method is a double exponential smoothing method (not based on ARIMA approach) which has two parameters. This method divides the time series into two sections: the level and the trend denoted by B_t and M_t respectively. These two parts are as follows:

$$B_t = \alpha X_t + (1-\alpha)(B_{t-1} + M_{t-1}) \tag{8}$$

$$M_t = \gamma(B_t + B_{t-1}) + (1-\gamma) M_{t-1} \tag{9}$$

The in-future forecasts values X_{t+h} of the time series can be calculated by:

$$X_{t+h} = B_t + M_t(h) \tag{10}$$

where*h* is the number of periods in the future. Diverse statistical meaning-making models in the R-language platform were used to evaluate the time series of infected cases and deaths for prediction purposes.

3. Results and Discussion

We present results for 10-day ahead forecasts (May 20 to May 29, 2020) generated for the cumulative number of infected cases and deaths in India as well as in the ten most affected states: Kerala, Maharashtra, Delhi, Gujarat, Tamil Nadu, Telangana, Uttar Pradesh, Madhya Pradesh, Karnataka, Rajasthan. In this work, we used two models Holt's method and ARIMA model to forecast the cumulative infected cases and deaths of COVID-19. For the ARIMA model, we forecast per day new infected case(s) and new death(s), whereas for Holt's method cumulative numbers are generated.

3.1 Validation: As of 22 April 2020, there were 21370 cumulative numbers of infected cases and 681 cumulative numbers of deaths in India. For validation purposes, we forecasted the cumulative number of infected cases and deaths from April 22 to May 1, 2020 using ARIMA and Holt's method. Our forecasting results showed 36335 [PI 95% ((30884, 42918))] cumulative number of infected cases using ARIMA(1,1,2) model and 36624 [PI 95% (30716, 43051)] cases using Holt's method (α=0.9, β=0.3), in both cases the 95% prediction intervals includes the actual values. While forecasting results of the cumulative number of deaths are 1140 [PI 95% (945, 1354)] using Holt's method (α=0.8, β=0.2) and 1099 [PI 95% (959, 1553)] using ARIMA(0,1,3) both the intervals includes the actual value, 1223 deaths by 1 May 2020, within 95% prediction interval. When necessary the Box-Cox transformation was used to stabilize the variance in Holt's and ARIMA models.

3.2 India forecasting:

3.2.1 ARIMA model: During the analysis and forecasting of a time series, it is good to plot the time series data and pay attention to the unique features exhibited by the time series. It gives direction to the researcher for choosing an appropriate modeling approach that directly captures identified features. Before starting the procedure, there is a need to make the time series stationary. To stabilize the variance, we used square root transformation on the infected number of cases per day time series. For investigating the stationarity of time series, we take the support of the KPSS and ADF test, and results are shown in Table 1. The first difference of series, i.e. d=1, is optimum to make series reasonably stationary. Based on a 5% significance level both the tests, ADF and KPSS, reject the hypothesis of stationarity of time series without making any difference. Afterwards taking the first difference, both the criteria agree on the stationarity of time series. Further, to estimate another two parameters of the candidate model, the ACF and PACF of series, first difference, and square root transformation are used. From Figure 2(a) and 2(b), the ACF display one spike, and the PACF also displays one spike. Initially, on the bases of the number of spikes, we selected ARIMA(1, 1, 1). Alternate models are also used to compete with the ARIMA(1,1,1) model. All alternative models and their AIC values with the Ljung-Box test p-values are shown in Table 2. A model with a minimal amount of AIC is to have well-behaved residuals. Finally, we select ARIMA(1,1,2) for forecasting. In terms of the residuals, the ARIMA(1,1,2) model passed the Ljung-Box test with p-values larger than 0.05 level of significance. Since ARIMA(1,1,2) has the lowest AIC value, which means the residuals of ARIMA(1,1,2) are much well behaved compared to other considered models. We examine that all the residuals are scattered around zero mean with constant variance. Using this, ARIMA(1,1,2) model observe 36335.53 [95% PI(30884.56 -42918.87)] cumulative infected cases between by 1 May2020, results are shown in Table 3.

Table 1: Table of p-values from ADF and KPSS tests after taking the differences of square root transformed data for infected cases per day in India.

Number of Difference	ADF test (p-value)	KPSS test (p-value)
d=0	0.961	0.01

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d=1	0.01	0.058

Table 2: Potential models for infected cases per day with AIC value and Ljung-Box test p-value.

Model	AIC value	Ljung-Box test (p-value)
ARIMA (0,1,2)	427.77	0.263
ARIMA (1,1,2)	418.82	0.518
ARIMA (0,1,1)	428.05	0.341
ARIMA (1,1,1)	428.59	0.258
ARIMA (1,1,3)	420.72	0.438

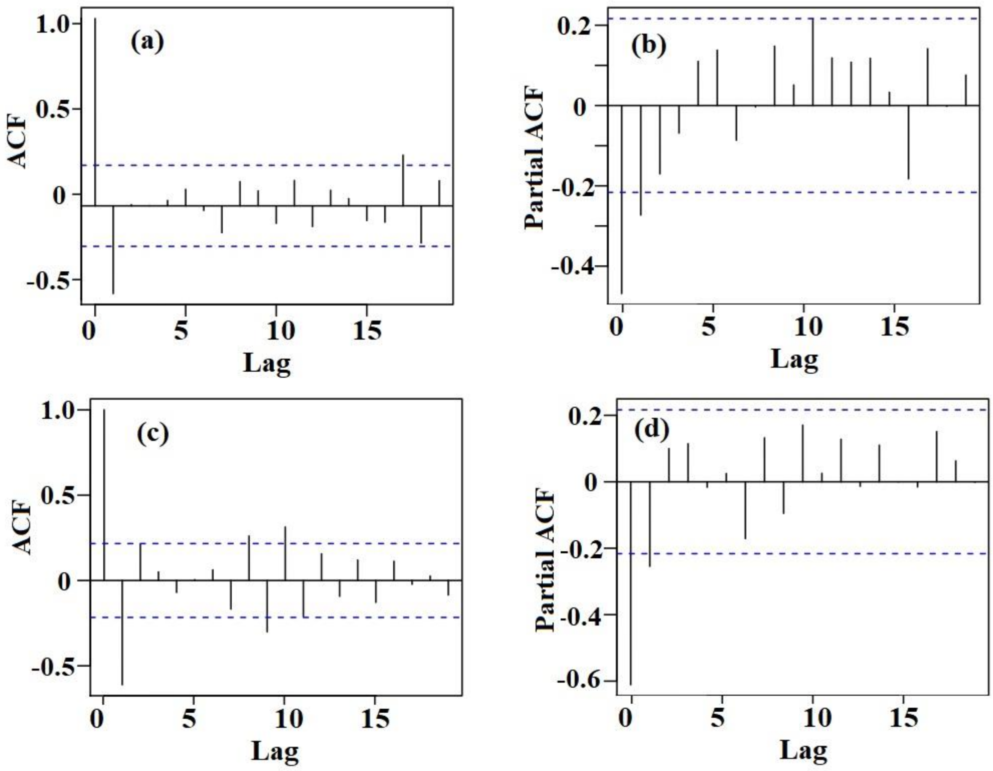

Figure 2: (a) ACF for the infected number of cases per day after square root transformation; (b) PACF for the infected number of cases per day after square root transformation; (c) ACF for the number of deaths per day; (d) PACF for the number of deaths per day.

Table 3: Results of 10-days ahead forecasts (22 April to 1 May 2020) using ARIMA model for the cumulative number of infected cases and deaths.

Date	Forecast of cumulative cases	95% PI for infected cases	Forecast of deaths per day	95% PI for deaths
22 April 2020	21507.35	(21099.49, 21983.68)	680.46	(671.04, 1004.66)
23 April 2020	22980.52	(22145.61, 23956.81)	727.64	(708.79, 1061.28)
24 April 2020	24498.87	(23213.42, 26004.80)	772.26	(741.49, 1117.82)
25 April 2020	26061.76	(24297.82, 28133.38)	817.41	(773.69, 1175.92)
26 April 2020	27668.50	(25393.68, 30348.45)	863.09	(805.46, 1235.49)
27 April 2020	29318.42	(26496.10, 32655.88)	909.29	(836.87, 1296.49)
28 April 2020	31010.80	(27600.44, 35061.35)	956.02	(867.97, 1358.85)

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29 April 2020	32744.95	(28702.47, 37570.28)	1003.28	(898.79, 1422.54)
30 April 2020	34520.13	(29798.33, 40187.84)	1051.06	(929.39, 1487.52)
1 May 2020	36335.63	(30884.56, 42918.87)	1099.38	(959.77, 1553.76)

Since only one difference makes the time series stationary, we conclude to take *d*=1. Results of ADF and KPSS tests are presented in Table 4. From Figure 2(c) and 2(d), ACF demonstrates two significant spikes, and PACF demonstrates zero significant spike. Based on the number of spikes, we selected ARIMA (0, 1, 2). Alternate models were also used to compete with the ARIMA (0,1,2) model. Details of other potential models along with AIC values and Ljung-Box test *p*-values given in Table 5. Furthermore, to forecast the number of deaths per day in India, we found ARIMA (0,1,3) a reasonable model among other competitor models it has minimum AIC value. Furthermore, we found residuals are randomly scattered around zero mean with non-changing variance with time. Also, ARIMA(0,1,3) does not show a lack of fit with the Ljung-box test *p*-value larger than 0.05. Graphical results of forecasting from infected cases and deaths are shown in Figure 3. Applying ARIMA(0,1,23), 1099.38 [95% PI(959.77-1553.76)] cumulative deaths are expected in coming 10 days in India. Results for 10-day ahead forecast for per day infected cases, and deaths are shown in Table 3. To eliminate the effect of square root transformation in per day infected cases we take a square of forecasted observations.

Table 4: Table of *p*-values from ADF and KPSS tests for deaths per day in India.

Number of Difference	ADF test (*p*-value)	KPSS test (*p*-value)
d=0	0.979	0.01
d=1	0.01	0.058

Table 5: Potential models for deaths per day data with AIC values and Ljung-Box test *p*-values.

Model	AIC value	Ljung-Box test (*p*-value)
ARIMA (0,1,3)	497.32	0.408
ARIMA (1,1,4)	499.79	0.208
ARIMA (0,1,2)	498.10	0.248
ARIMA (1,1,2)	498.77	0.274
ARIMA (1,1,3)	498.41	0.365

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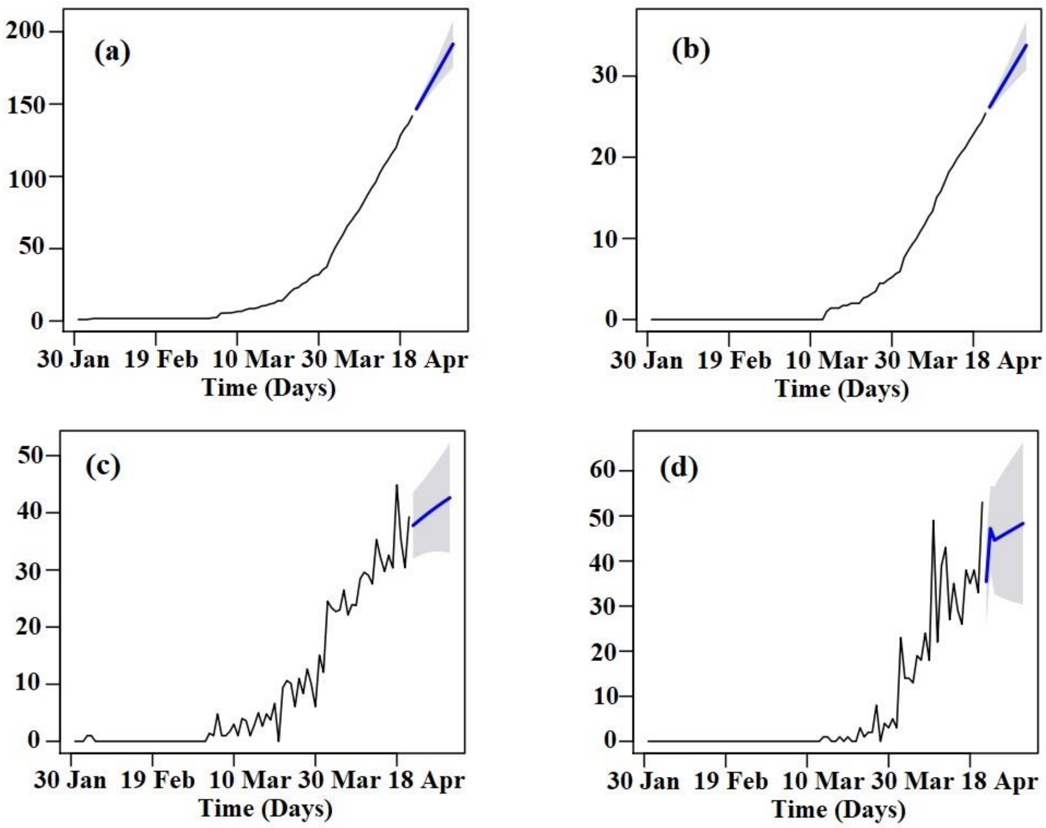

Figure 3: (a)10-days ahead forecast (22 April to 1 May 2020) for the number of infected cases per day using ARIMA(1,1,2) model; (b) 10-days ahead forecast (22 April to 1 May 2020) for the number of deaths per day using ARIMA(0,1,3) model; (c) 10-days ahead forecast (22 April to 1 May 2020) using Holt's method for the cumulative number of infected cases; (d) 10-days ahead forecast (22 April to 1 May 2020) for the cumulative number of days using Holt's method.

3.2.2 Holt's Method: The time series plot of the cumulative number of confirmed cases and deaths for India is presented in Figure 1 exhibiting the trend in time series, but it does not have a pattern of seasonality. As a result of the features shown by time series in Figure 1, Holt's method was selected in this study to accomplish a 10-day ahead forecast (May 20 to May 29, 2020). Generally, a Holt method has two smoothing constants, α and β (their values lie in range 0 and 1). The square root transformation is used to stabilize the variance in the time series of infected cases. In the process to attain the optimal parameters we applied by trial and error technique. Results are shown in Table 6 with the value of α, β, AIC, and RMSE values. The best model is selected with the lowest AIC and RMSE values. With the parameters, α=0.9 and β=0.3, obtained values of AIC and RMSE are 381.02 and 1.05, respectively. For this model, Ljung-Box test *p*-value=0.468 which agrees that model does not exhibit any lack of fit.

Using Holt's method, different values of α and β are tried to retrieve the optimum forecast for cumulative deaths. The square root transformation is used to stabilize the variance in the time series of deaths. The results of the trials are listed in Table 7 with AIC and RMSE values. Smallest values of AIC=151.78 and RMSE=0.26 at α=0.8 and β=0.2 are achieved. Subsequently, checking the Ljung-Box test *p*-value=0.109 we identify that model does not lack of fit. Graphical results of forecasting from infected cases and deaths are presented in Figure 3. From Table 8, 36624.43 [95% PI(30716.59-43051.56)] cumulative infected cases and 1140.70 [PI % (945.32-1354.42)] cumulative deaths are in India up-to 1 May2020.

Table 6: Selection process for parameters in Holt's method to forecast the cumulative number of infected cases in India.

α	β	AIC value	RMSE
0.1	0.1	503.15	2.19
0.5	0.1	435.19	1.46
0.5	0.5	400.55	1.18
0.9	0.5	383.37	1.06
0.9	0.3	381.02	1.05

Table 7: Selection process for parameters in Holt's method to forecast the cumulative number of deaths.

α	β	AIC value	RMSE
0.1	0.1	253.11	0.49
0.5	0.1	185.53	0.32
0.5	0.5	167.63	0.29
0.9	0.5	157.12	0.27
0.8	0.2	151.78	0.26

Table 8: Results of 10-days ahead forecasts (22 April to 1 May 2020) using Holt's method for the cumulative number of infected cases and deaths.

Date	Forecast of cumulative infected cases	95% PI for infected cases	Forecast of cumulative deaths	95% PI for deaths
22 April 2020	21498.39	(20883.67, 22122.02)	685.95	(658.43, 714.02)
23 April 2020	22981.26	(21992.15, 23992.12)	730.79	(690.78, 771.94)
24 April 2020	24513.58	(23102.62, 25966.35)	777.06	(723.16, 832.91)
25 April 2020	26095.35	(24209.69, 28051.72)	824.75	(755.44, 897.10)
26 April 2020	27726.57	(25311.47, 30251.70)	873.86	(787.58, 964.62)
27 April 2020	29407.24	(26407.03, 32568.84)	924.39	(819.55, 1035.54)
28 April 2020	31137.36	(27495.78, 35005.34)	976.34	(851.32, 1102.92)
29 April 2020	32916.93	(28577.24, 37563.27)	1029.71	(882.88, 1187.82)
30 April 2020	34745.95	(29650.98, 40244.67)	1084.49	(914.22, 1269.30)
1 May 2020	36624.43	(30716.59, 43051.56)	1140.70	(945.32, 1354.42)

3.3 Indian states forecasting:

COVID-19 is spreading very fast in India. Locating the regions of most spread within India will give insight for the lifting the lockdown which commenced on 25 March 2020. On the regional level, this study shows the analysis for the cumulative number of cases but not deaths due to the unavailability of data. A glimpse of the current situation of the increasing number of cases in 10 states is given in Figure 4, certainly detectable that Maharashtra, Gujarat, and Delhi are the most affected states in India till April 21, 2020. And Kerala is least affected in our list of states. Time series starts from the date when the first case was reported in the respective state.

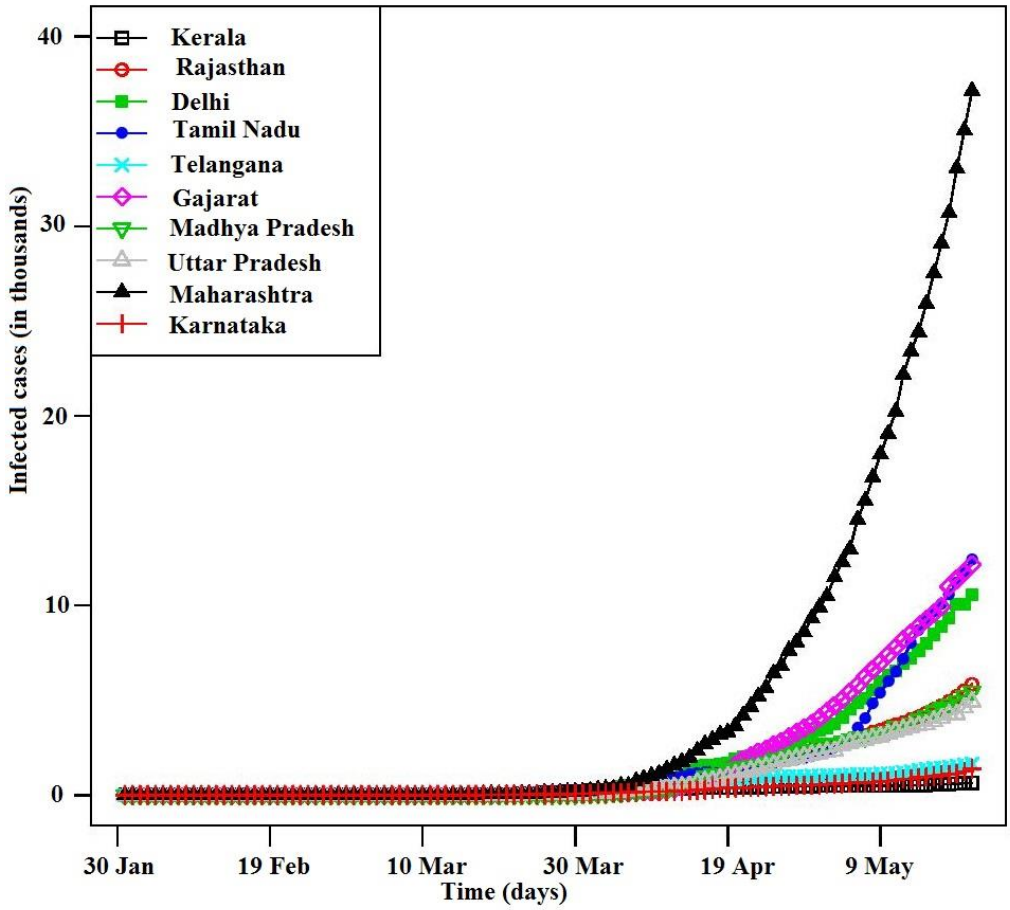

Figure 4: Number of infections in the ten most affected Indian states by corona-virus as of 30 January to 20 May 2020.

3.3.1 ARIMA model: For forecasting purposes, using the ARIMA model, the number of newly infected cases per day are analyzed instead of cumulative infected cases. To select the optimum ARIMA model for each state, firstly each state's time series is made stationary by taking differences. Next, we used ADF and KPSS tests to check stationarity. To stabilize the variance of Delhi, Telangana, Uttar Pradesh, and Gujarat time series, cube root transformations are used; later, one difference is enough to remove the trend. While to stabilize the variance of Maharashtra, Karnataka and Rajasthan time series, square root and square transformations are used, respectively. The same procedure is adopted for all the ten-time series of infected cases per day. AIC values are used to select the best models, and the model is chosen on the base of the smallest AIC value. Results of analysis for ARIMA models are shown in Table 9. Analysis by ARIMA models shows that Maharashtra and Gujarat will be the most affected states by 1 May 2020, with around 9787.24 and 4216cumulative cases, respectively. As we observe that Kerala's growth is declining and it will be less affected states with 449 [PI 95%(408-574.99)] cumulative cases. All the models passed the Ljung-Box test as well as does not show any lack of fit.

Table 9: Region-wise details of ARIMA models which were used for 10-days ahead forecasts (22 April to 1 May 2020), along with AIC values and Ljung-Box test *p*-values. Point forecasts and 95% prediction intervals are given in the last two columns.

Region	ARIMA Model	AIC value	Ljung-Box test	Point forecast for	95% PI for infected cases

			(*p*-value)	infected cases	
Kerala	(2,1,0)	498.53	0.329	449.38	(408, 574.90)
Maharashtra	(0,1,2)	233.65	0.807	9787.24	(6949.81, 13757.06)
Rajasthan	(0,1,1)	947.38	0.147	2741.40	(2305.22, 3053.91)
Delhi	(1,1,2)	177.46	0.064	3039.73	(2139.72, 6085.18)
Telangana	(2,1,0)	133.99	0.112	1321.37	(940.84, 2740.89)
Karnataka	(3,1,0)	160.03	0.371	565.74	(419.09, 945.45)
Gujarat	(0,1,0)	89.76	0.131	4216.00	(2216.24, 13118.90)
Uttar Pradesh	(2,1,1)	140.25	0.161	2652.21	(1612. 43,4891.99)
Tamil Nadu	(1,1,1)	440.69	0.840	2157.35	(1520, 2878.82)
Madhya Pradesh	(0,1,1)	340.62	0.961	2281.84	(1540, 3688.99)

3.3.2 Holt's method: Square root transformation is used to stabilize the variance of Rajasthan, Maharashtra, Karnataka,and Uttar Pradesh. The cube root and square transformation are used for Delhi, Kerala, Telangana, and Gujarat, respectively. Summary of Holt's method display that Maharashtra and Delhi will be most affected states with around 9768.91 and 3768.39cumulative number of infected cases, respectively. Meanwhile, Kerala will be the less affected state in our list with about 451.67 cumulative number of infected cases. The selection of optimum Holt's method is performed using the minimum values of AIC and RMSE. Although, all the model passed the Ljung-Box test, which state that model does not show any lack of fit. Results of the forecast for each state are given in Table 10 with Ljung-Box test *p*-values. The final graphical results of the analysis using both the models, ARIMA model, and Holt's method, are shown in Figures 5-11.

Table 10: Region-wise 10-days ahead forecasts (22 April to 1 May 2020) details of Holt's method, along with Ljung-Box test *p*-values. Point forecast and 95% prediction intervals are given in the last two columns.

Region	Ljung-Box test (*p*-value)	Point forecast for infected cases	95% PI for infected cases
Kerala	0.134	451.67	(408, 858.58)
Maharashtra	0.776	9768.91	(7453.81, 12396.63)
Rajasthan	0.073	2978.53	(1921.79, 4265.86)
Delhi	0.051	3768.39	(2081, 6607)
Telangana	0.029	1424.42	(919, 3171.29)
Karnataka	0.166	602.05	(495.65, 708.44)
Gujarat	0.229	3562.28	(2992.38, 4052.81)
Uttar Pradesh	0.138	2569.51	(1773.49, 3512.69)
Tamil Nadu	0.635	2158.51	(1664.95, 2652.07)
Madhya Pradesh	0.162	2301.68	(1540, 3321.74)

3.4 Recommendations on Lockdown Extension: India comprises 28 states and eight union territories. Here we have analyzed all the states, including five union territories. In Figure 12, the spatial distribution of coronavirus outbreak shows eight states in the red zone (extremely affected), namely, Delhi, Rajasthan, Uttar Pradesh, Maharashtra, Telangana, Karnataka, Kerala, Tamil Nadu.
Similarly, seven states in the blue zone (intermediate affected), are Jammu & Kashmir, Punjab, Haryana, Gujarat, Madhya Pradesh, Andhra Pradesh, West Benga. The green and light green (least affected) zones include Himachal Pradesh, Uttrakhand, Bihar, Jharkhand, Chhattisgarh, Odisha, Sikkim, Arunachal Pradesh, Assam, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Goa. To construct the zones, we have divided the cumulative cases of states into quartiles as on 1 April 2020.

The same procedure is carried out for forecasted cumulative cases until 1 May 2020. As infected cases are increasing, it is essential to notice which of the states will shift their zone.

Figure 13 shares Delhi, Rajasthan, Uttar Pradesh, Gujarat, Madhya Pradesh, Maharashtra, Telangana, Tamil Nadu in the red zone and Jammu & Kashmir, Punjab, Haryana, Kerala, Karnataka, West Bengal in the blue zone while Himachal Pradesh, Goa, Uttrakhand, Bihar, Jharkhand, Chhattisgarh, Odisha, Sikkim, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya are in green and light green zones.

It is found that Kerala and Karnataka were in the red zone, and Gujarat and Madhya Pradesh were in the blue area until 1 April 2020 (Figure 12). But they are likely to change their positioning by 1 May. Accordingly, Kerala and Karnataka will shift to the blue zone as cases are declining in both states. Conversely, Gujarat and Madhya Pradesh will move to the red area. Recent 10 days ahead forecast from 20 May to 29 May 2020 show that there will outburst of infected cases in seven Indian states all the seven states are in the list of most affected states. Forecasting results of all the states by 29 May 2020 are shown in Table 11 along with outburst expected states. The government should impose extra precautions in these states, as the cases will significantly rise in both in the coming days. While lockdown should remain in the red zone, conversely, the blue area is not remarkably affected by COVID-19, so lockdown should be lifted with some restrictions. It is advisable to lift the lockdown in states within green and light green zones for the proper functioning of the economy. Also, we divided the states based on cumulative cases that lie in one, two, and three standard deviations from the overall mean (taken over all the states of India). Based on which we conclude that states which have cases more than three standard deviations are expected to face outburst of infected cases by 29 May 2020. While the states with cumulative cases lesser than one standard deviation will be less affected by COVID-19 as shown in figure 14. Percentage error of validation for India and ten most affected states shown in Table 12. Holt's method gives a 1.96% error for cumulative infected cases of India which more precise than the ARIMA model. While for Rajasthan, Maharashtra, Telangana, Gujarat, and Karnataka ARIMA model gives more precise results compare to Holt's method.

Further, analysis of red and blue zones at the regional level is of importance to decide about raising the district wise lockdown.

Table 11: 10 days ahead forecast for Indian states from May 20 to May 29, 2020.

State	**Point Forecast**	**Lower Bound**	**Upper Bound**	**Mean**	**SD**
Kerala	826	723	930	214.0089286	220.4974513
Maharashtra	62628	52840	73555	4898.6875	8954.145967
Rajasthan	9336	5845	14198	1001.517857	1548.865758
Delhi	15337	12595	18349	1648.410714	2739.833994
Telangana	2037	1634	2471	403.8482143	518.2371924
Karnataka	2354	1934	2814	243.1785714	340.1449139
Gujarat	17164	13580	21167	1805.160714	3217.772739
Uttar Pradesh	7059	5880	8346	870.4107143	1348.852489
Tamil Nadu	19777	13954	26613	1567.044643	2954.255188
Madhya Pradesh	7876	5864	10184	965.2678571	1506.346418
Haryana	1303	1026	1614	175.7857143	262.4089865
Himachal Pradesh	149	92	252	18.33928571	24.45939955
Jammu & Kashmir	1902	1610	2219	252.1160714	364.3831205
Punjab	2195	2002	6378	332.25	623.1226724
Uttarakhand	195	151	240	23.05357143	28.76209946
Bihar	3071	1779	4872	173.0446429	328.291191
Jharkhand	373	277	489	37.78571429	63.72949995

Chhattisgarh	134	101	186	18.47321429	24.85995362
Odisha	2150	1104	3707	91.40178571	193.9879935
Andhra Pradesh	3187	2532	4235	516.2053571	769.7394334
West Bengal	4574	3911	5309	409.3660714	750.7096222
Assam	736	185	1650	20.27678571	28.71895812
Manipur	27	11	49	1.160714286	1.568574101
Tripura	210	173	399	18.72321429	48.151265
Meghalaya	13	13	19	3.8125	5.604906554
Arunachal Pradesh	1	1	1	0.428571429	0.497095813
Pondicherry	24	18	37	3.794642857	4.540386126
Goa	245	143	374	4.339285714	6.84388801
Chandigarh	292	200	425	34.01785714	58.51387487
Mizoram	1	1	1	1	0
				525.0970238 (Overall Mean)	1775.322896 (Overall SD)

Table 12: Percentage error of cumulative numbers of cases for India and ten most effect states using both the method, ARIMA model and Holt's method, shown.

		Forecasted Values		**Percentage Error**	
Location	**Actual Values**	**ARIMA model**	**Holt's method**	**ARIMA model**	**Holt's method**
India	37257	36335	36624	2.47	1.96
Kerala	497	779	451	9.65	9.25
Maharashtra	10498	9787	9768	6.77	6.95
Rajasthan	2584	2741	2978	6.07	15.24
Delhi	3515	3039	3768	13.54	7.19
Telangan	1039	1321	1424	27.14	37.05
Karnataka	576	565	602	1.90	4.51
Gujarat	4395	4216	3562	4.07	18.95
Uttar Pradesh	2281	2652	2569	16.26	12.62
Tamil Nadu	2323	2157	2158	7.14	7.10
Madhya Pradesh	2719	2281	2301	16.10	15.37

4 Conclusions

The spread of the COVID-19 epidemic has been slow in India as compared to other countries like Italy and the USA. It reflects the influence of the broad spectrum of social distancing measures put in use by the government of India, which has played the role of a barrier to growing infected cases and deaths, apparently helped to slow down the epidemic growth. Our short-term forecast reveals that at the regional level, Delhi, Rajasthan, Gujarat, Maharashtra, Uttar Pradesh, Madhya Pradesh and Tamil Nadu will be the most affected states in the coming days which is confirmed by both quartile and standard deviation procedures as shown in Figures 13-14. Considering the situation, lockdown should not be lifted in these states. The number of cases in Kerala and Karnataka are found to be reducing. Moreover, these states are shifted from the red zone to blue. Since very little growth in the future is predicted, lockdown may be lifted in these states with some restrictions for the proper functioning of economic activities. While states in green and light green zones, namely, Himachal Pradesh, Goa, Uttrakhand, Bihar, Jharkhand, Chhattisgarh, Odisha, Sikkim, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya show very less growth in the infected

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cases till 1 May, therefore, lockdown may be uplifted there. On India level, there will be around 169109 [95% PI(144426, 196455)] cases and 4863 [95% PI(4221, 5551)] deaths up to 29 May 2020. The forecasts presented here are based on the assumption that current mitigation efforts will continue.

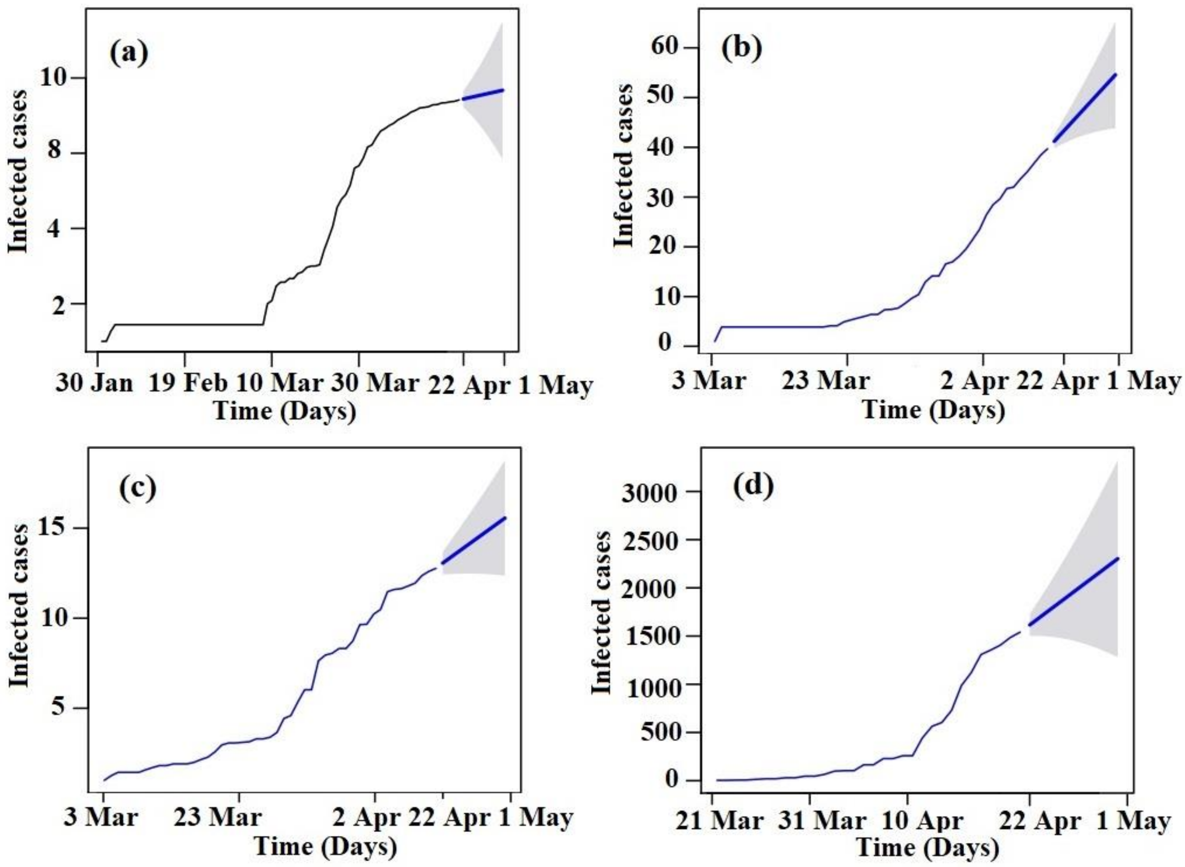

Figure 5: (a) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Kerala; (b) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Rajasthan; (c) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Delhi; (d) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Madhya Pradesh.

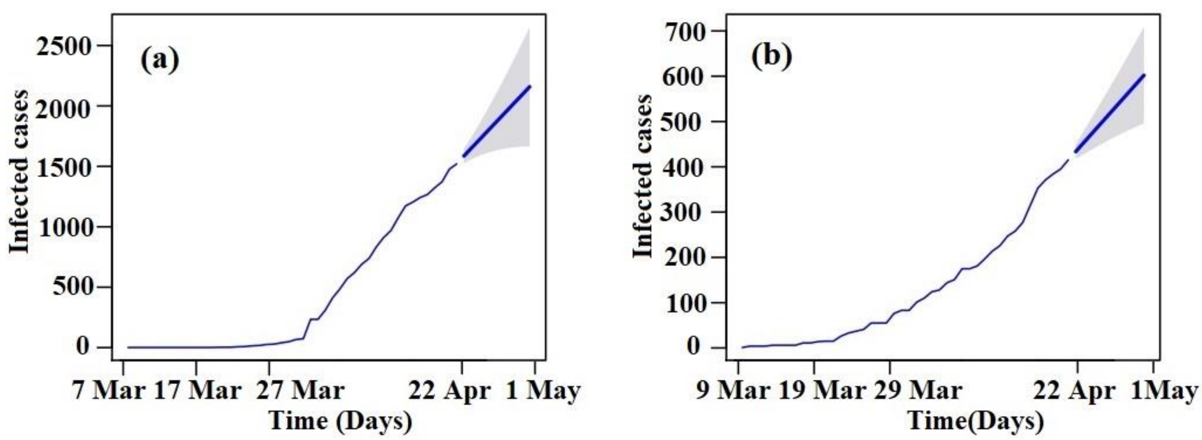

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Figure 6: (a) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Tamil Nadu;(b) 10-days ahead forecast (22 April to 1May 2020) using Holt's Method for Karnataka.

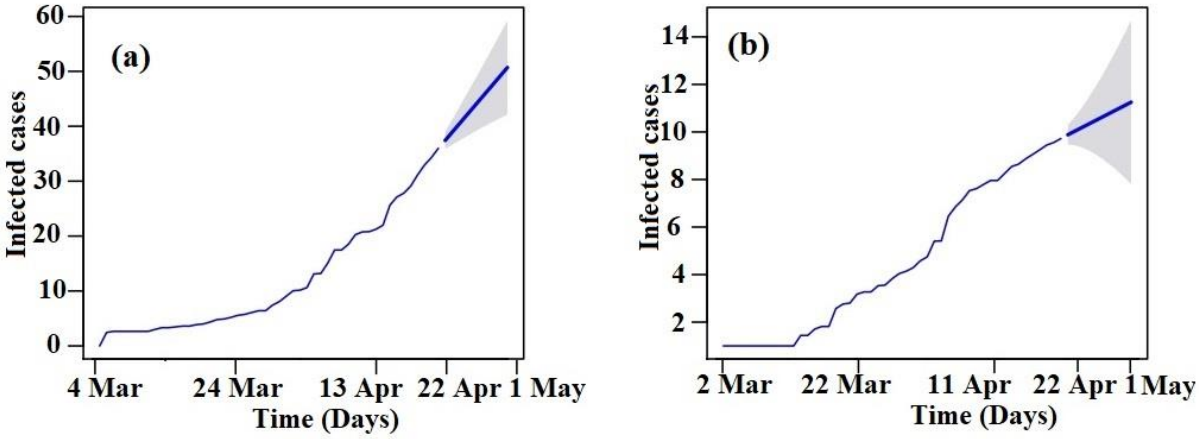

Figure 7: (a)10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Uttar Pradesh; (b) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method forTelangana.

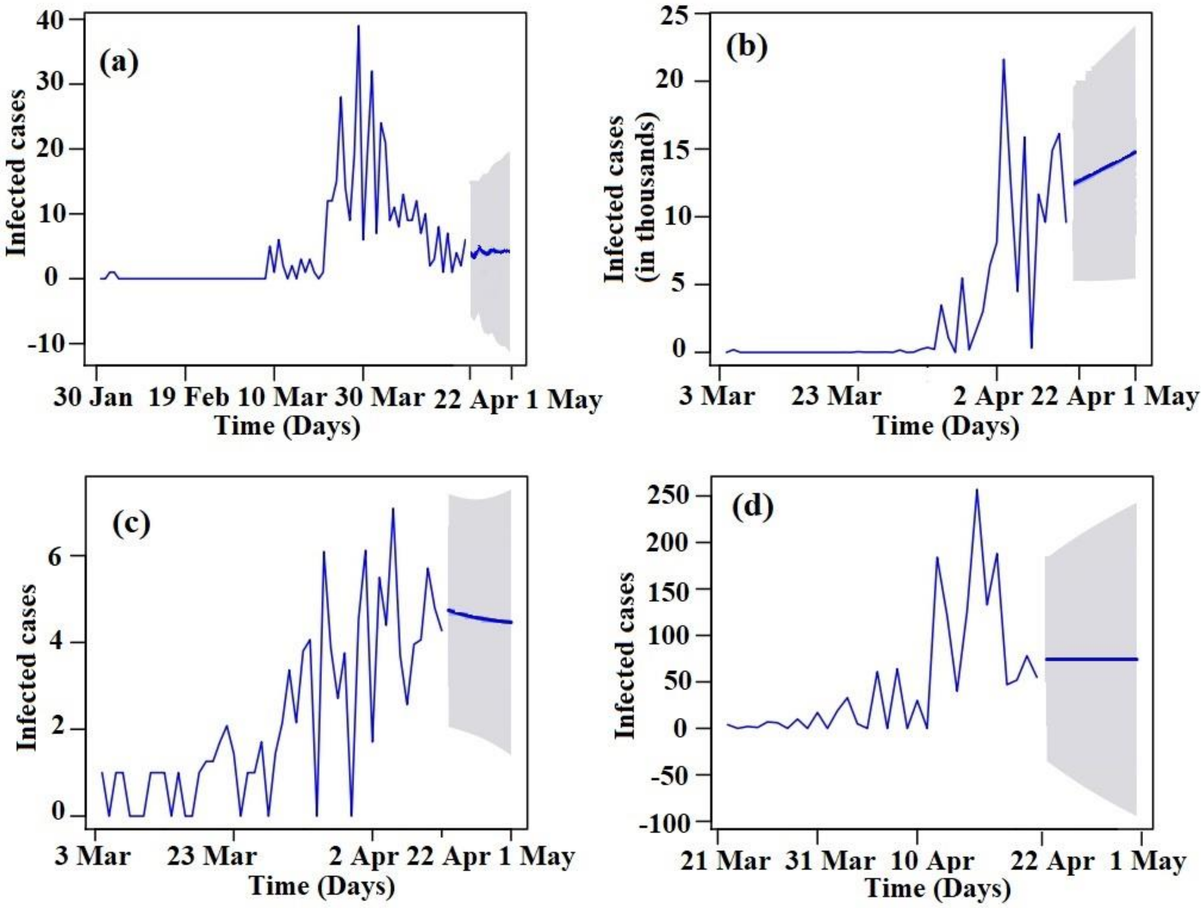

Figure 8:(a) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(2,1,0) model for Kerala; (b) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(0,1,1) model for Rajasthan; (c) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(1,1,2) model for Delhi; (d) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(0,1,1) model for Madhya Pradesh.

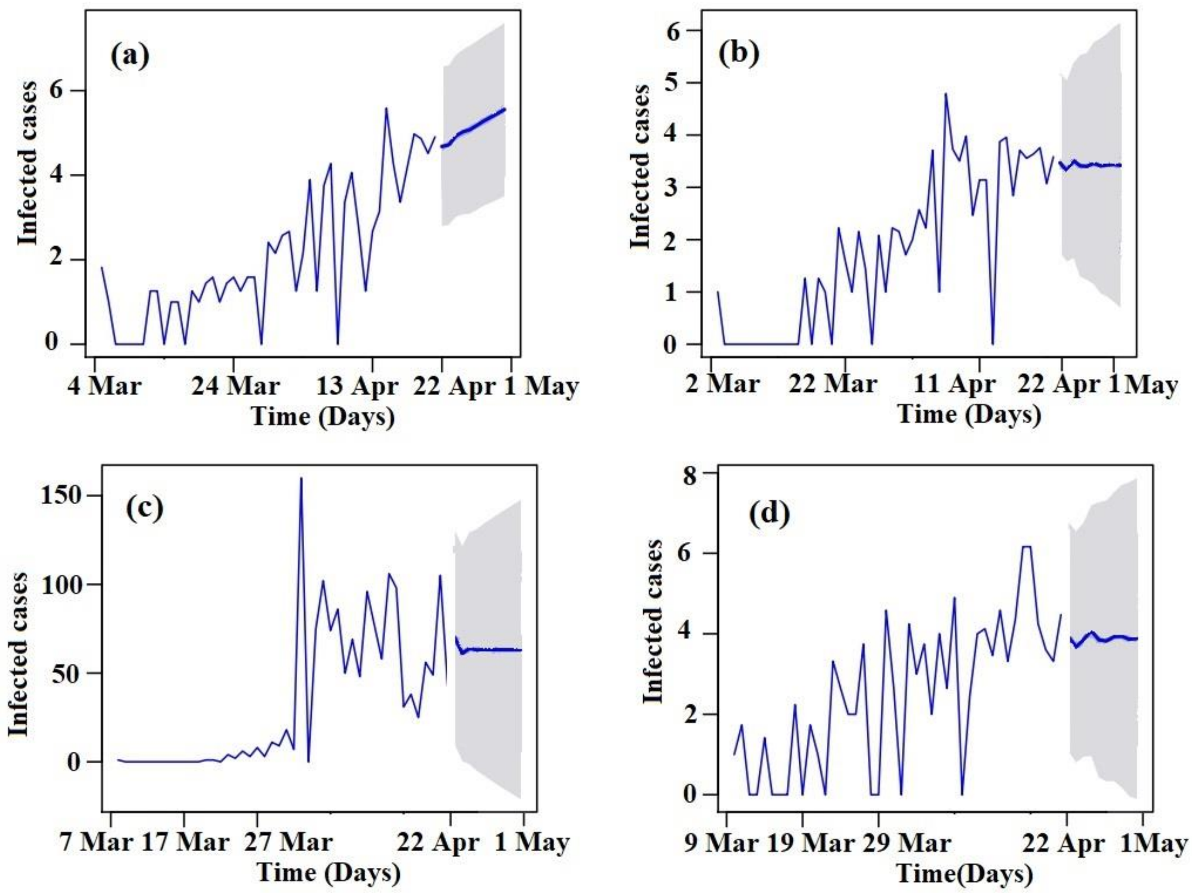

Figure 9:(a) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(2,1,1) model for Uttar Pradesh; (b) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(2,1,0) model for Telangana; (c) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(1,1,1) model for Tamil Nadu; (d) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(3,1,0) model for Karnataka.

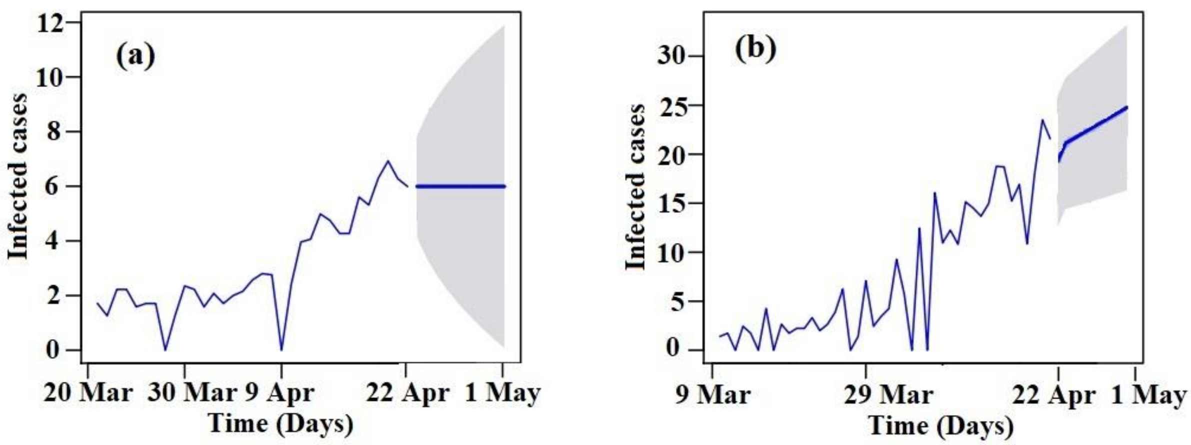

Figure 10: (a) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(0,1,0) model for Gujarat; (b) 10-days ahead forecast (22 April to 1 May 2020) using ARIMA(0,1,2) model for Maharashtra.

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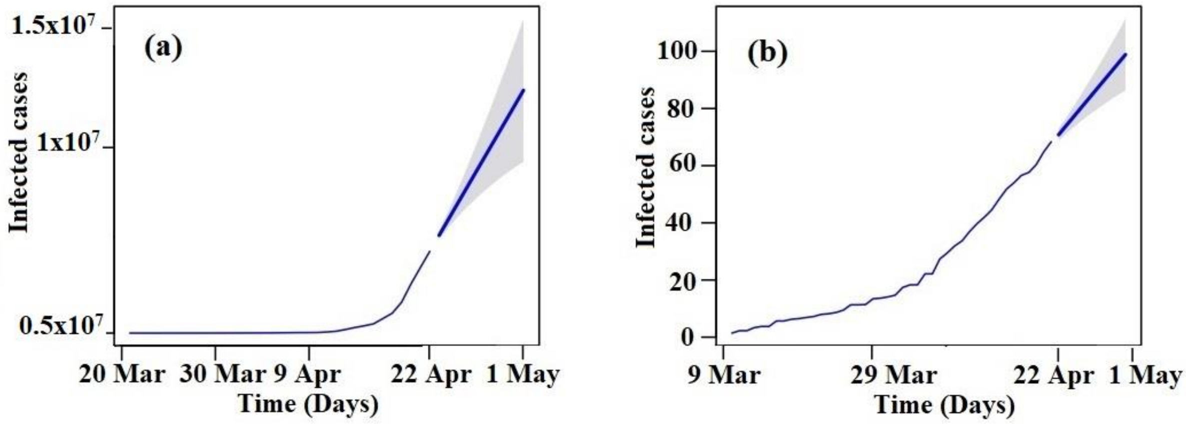

Figure 11: (a) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Gujarat; (b) 10-days ahead forecast (22 April to 1 May 2020) using Holt's Method for Maharashtra.

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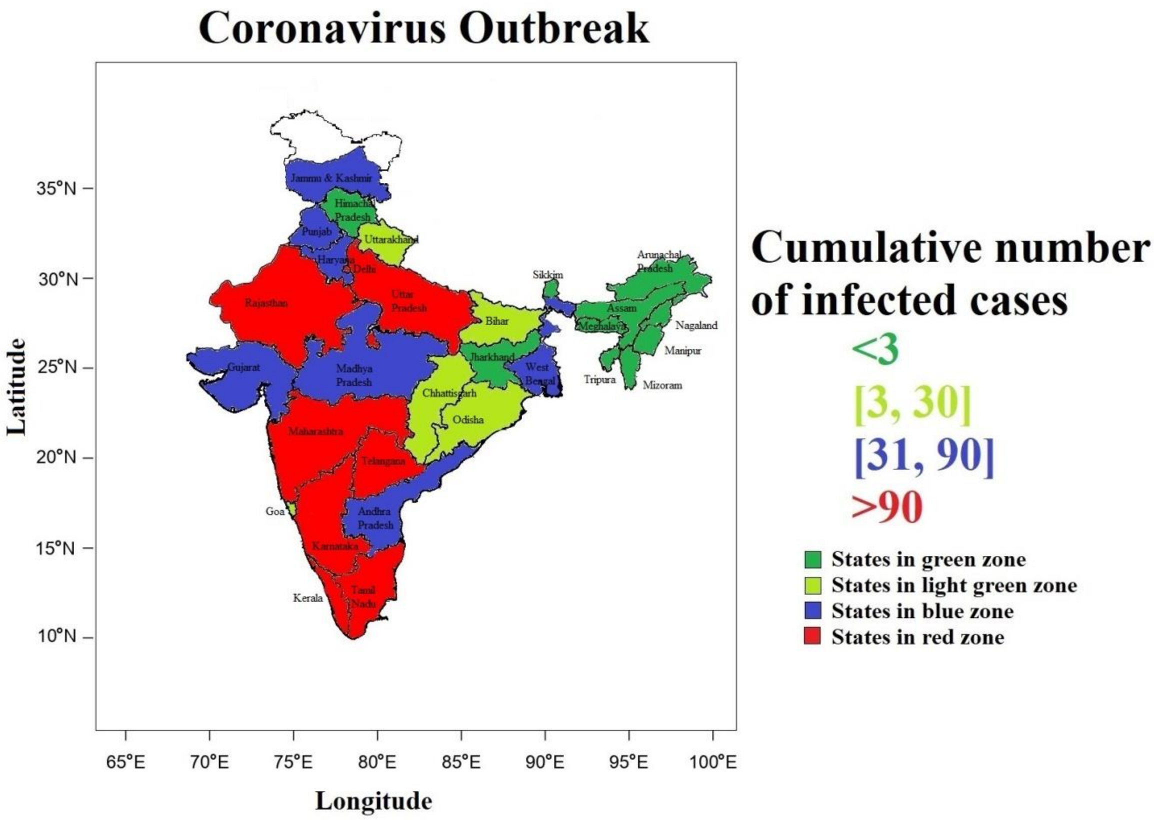

Figure 12: Spatial distribution of the coronavirus outbreak in the period of 30 Jan to 1 April 2020.

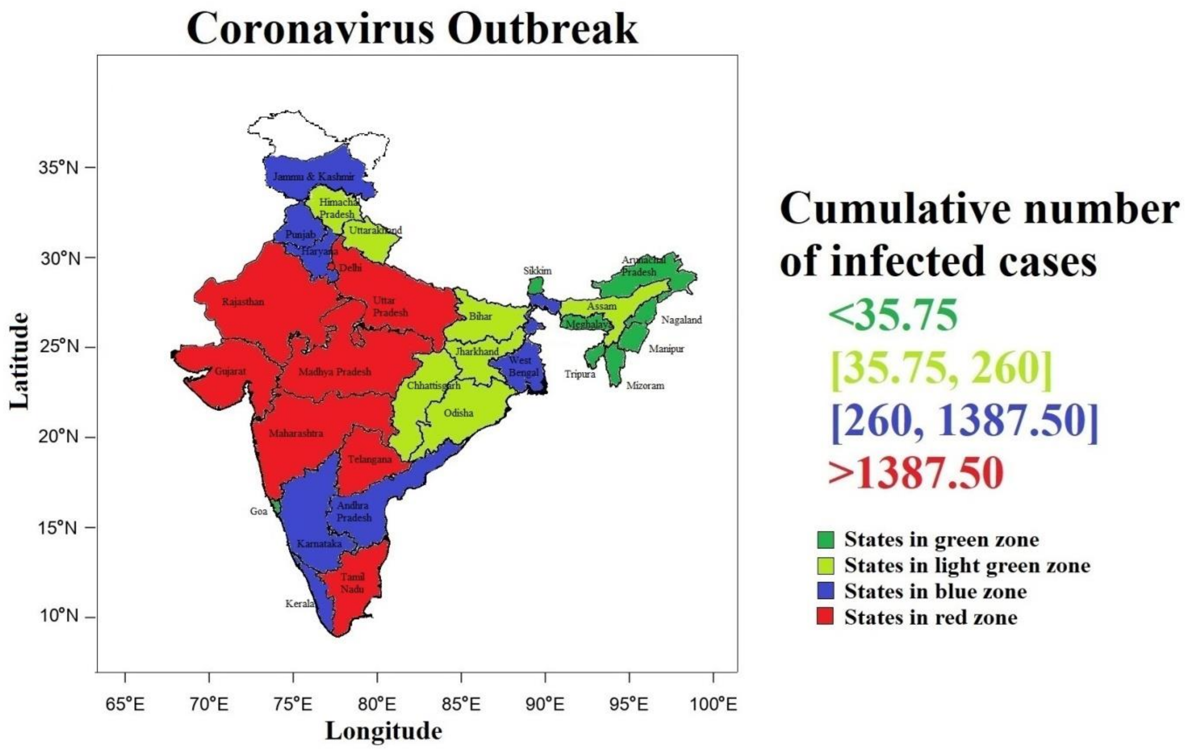

Figure 13: Spatial distribution of the coronavirus outbreak in the period of 30 Jan to 1 May 2020.

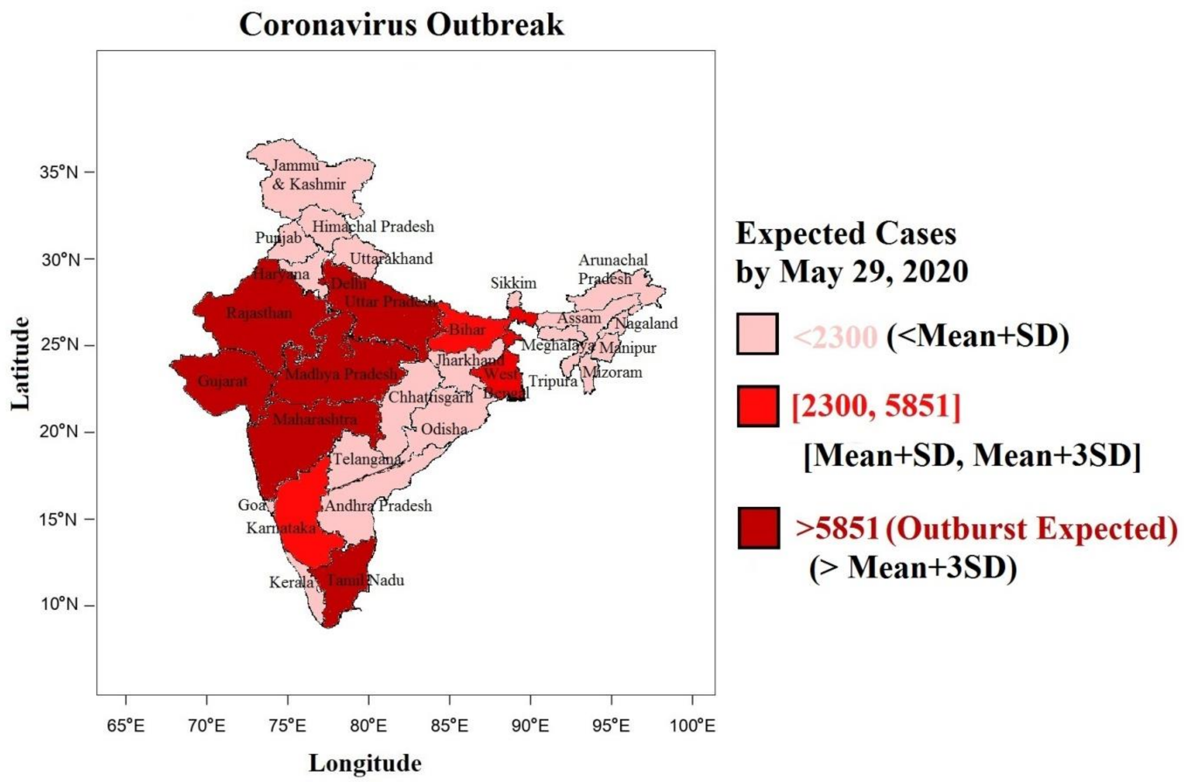

Figure 14: Expected numbers of cases in Indian states by May 29, 2020.

5 Data Availability

We obtained daily updates of the cumulative number of infected cases and deaths of the corona-virus illness for India from the Worldometer website (online available: https://www.worldometers.info/corona-virus/country/india/). To obtain the state-wise cumulative number of infected cases and deaths for the corona-virus illness we used the government of India website (online available: https://www.mygov.in/corona-data/covid19-statewise-status). We gathered data of infected case(s) every day at midnight (GMT-5) from 30 January to 21 April 2020. And forecasted the cumulative number of infected cases and deaths of the epidemic over the India and the cumulative number of infected cases in ten Indian states: Kerala, Maharashtra, Delhi, Gujarat, Tamil Nadu, Telangana, Uttar Pradesh, Madhya Pradesh, Karnataka, and Rajasthan, which show a high burden of COVID-19 cases.

6 Conflicts of Interest

The authors declare no conflicts of interest.

7 FundingStatement

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