



QUANTIFYING EPIDEMIC SPREAD THROUGH GROWTH TRAJECTORIES, RECOVERY DYNAMICS, AND TEMPORAL FORECASTING

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ARTICLE INFO

Received: 14/04/2026

Revised: 09/06/2026

Accepted: 11/07/2026

Published: 30/07/2026

DOI: <https://doi.org/10.69980/2db0cx07>

Volume:12, Issue:03, July, 2026

Abstract

Temporal variations of the incidence, recovery and mortality rates and the burden of active disease determine how an epidemic progresses. These indicators can be incorporated into forecasting to give a more comprehensive picture of the dynamics of an epidemic than cumulative case numbers. This study quantified epidemic spread through growth trajectories, recovery dynamics, associations among major indicators, and short-term temporal forecasting using longitudinal COVID-19 data from India. Daily cases of confirmed, recovered, and deceased patients were analyzed using a retrospective time-series design. The daily incidence, active cases, growth rate, recovery rate, case fatality rate and seven-day moving averages were calculated. Monthly patterns and Spearman correlations were examined, while ARIMA and Holt damped-trend models were evaluated using a chronological 80:20 training-testing split. The mean number of confirmed cases was 33,019.78 per day, and the recovery rate was 97.30% at the end of the study. Active cases peaked at 1,021,053 before declining substantially. The daily growth rate showed a strong inverse association with the recovery rate ($\rho = -0.968$). Holt damped trend achieved lower MAE (7,540.36) and RMSE (9,346.85) than ARIMA(2,1,3). Combining epidemic growth, recovery, association patterns and forecasting offers a unified picture for characterizing temporal evolution of an epidemic and assessing short-term predictive performance.

Keywords: epidemic growth, recovery dynamics, COVID-19, time-series forecasting, ARIMA.

1. Introduction

Epidemics of infectious diseases are defined as dynamic processes over time that go through distinct phases of transmission, recovery and mortality. These changes cannot be quantified by the number of cumulative cases alone, since the rate and direction of an epidemic may change as the number of contacts in a population may change and the circumstances of the transmission of the disease change. Mathematical modelling of COVID-19 showed that COVID-19 could have significant impacts on the course of the epidemic, with time-varying contact rates leading to acceleration or deceleration in the epidemic, often masked by assumptions that are not time-dependent (Kochańczyk et al., 2020). Additionally, when considering transmission suppression, there is a risk that it can be seen as a temporary phenomenon and not as a permanent one, as it can happen because of the presence of population heterogeneity (Tkachenko et al., 2021). Longitudinal surveillance can be used as a practical means of capturing these dynamics. Epidemic informatics combines the latest health information with analytical techniques to assist in the monitoring, response to, and risk management of an outbreak (Yang et al., 2020). Case information collected in a detailed and systematic manner is especially useful as it allows the systematic organization of information to follow changes in transmission over space and time (Xu et al., 2020). A longitudinal examination of changes in COVID-19 incidence during the second wave of the European epidemic also showed that it was important to consider changes in incidence over time, as well as the cumulative incidence burden (Post et al., 2021).

Other indicators can be used to capture the nature of an epidemic's spread. Daily incidence refers to the number of new cases being recorded each day, and growth rates refer to the rate of increase relative to the previous day. Moving averages smooth out short-term variations and show the overall trend. The dimensions of recovery and mortality, as well as active-case burden, add further dimensions, as these relate to the burden of disease that continues as a result of accumulated infections. However, estimates of the dynamics of an epidemic are sensitive to the surveillance process, such as how the epidemic is being monitored using tests and what is reported from the observed samples (Hay et al., 2021). The statistical analysis of epidemics has also highlighted that the transition between growth and decline is a key aspect of epidemic dynamics and must be explicitly characterized in time (Drake et al., 2019). The temporal patterns are explored using multiple methods for the study of COVID-19. Derakhshan et al. (2021) detected weekly periodicity in both infection and mortality time series and reported on both short- and longer-term variations within time-series, highlighting the need to consider recurrent variations in reported epidemic data. Mustavee et al. (2022) considered the early evolution of COVID-19 spread in a dynamical way and found that the COVID-19 trajectory was correlated with changes in human mobility, as a larger number of people traveled to and from the affected areas led to a greater spread of the disease. There is also an application of the growth-based method directly for short-term prediction, such as by Bartolomeo et al. (2021), who put in place an epidemic forecasting model for Italy, which used weighted and cumulative average daily growth rates.

Another way to derive short term estimates from historical observations of epidemics is time-series forecasting. The popularity of ARIMA models during COVID-19 was because they capture serial dependence from observed values and past errors, but do not have to be explicitly specified in detail. Sahai et al. (2020) fitted the ARIMA models with the daily observations of the series of COVID-19 cases in five highly infected countries and compared the forecasts with the subsequent observations. To illustrate the applicability of statistical forecasting to epidemic surveillance, Chyon et al. (2022) made use of the time-series analysis approach ARIMA to model and forecast the COVID-19 case pattern. Forecasting studies in India also demonstrated the need for short-term prediction in epidemic situations where changes in conditions are rapid. Working with daily data from four states in India, Khajanchi and Sarkar (2020) created a compartmental model to give projections of the daily and cumulative cases for a short window of time. These studies demonstrate that in addition to the traditional epidemiological analyses, temporal forecasting can also improve the quality of the analysis; however, the behaviour of the forecasts is still to be linked to the structure of the historical trajectory on which they rely.

Although there is a voluminous literature, growth characterization and recovery dynamics and forecasting have been treated as distinct analytical problems. Research focusing on incidence and transmission can offer little information about the evolution of recovery, and analysis for prediction may neglect describing the evolution that occurred before the prediction. In this way, the integrated longitudinal assessment can offer a more complete picture of the epidemic process, using the daily incidence, growth rates, smoothed trajectories, recovery, mortality, and active cases at any time, as well as associations between the epidemic indicators, and out-of-sample forecasting in a unified analytical framework.

In the present study, this gap is filled by quantifying the spread of epidemics by using the growth curves, recovery dynamics and temporal forecasting based on longitudinal observations of COVID-19 in India. The study aimed to quantify temporal changes in confirmed infections, deaths, recoveries, and active epidemic burden; characterize epidemic growth and recovery trajectories using temporal and statistical indicators; and develop and evaluate time-series models for short-term forecasting of epidemic trends.

2. Methodology

2.1 Research Design

A retrospective longitudinal time-series design was used to measure the spread of an epidemic by measuring change over time in the number of cases, recoveries, and the burden of disease. The types of analysis that were performed included descriptive time-series analysis, growth characterization, assessment of recovery, and short-term forecasting, based on daily aggregate observations. One key feature of the design was the use of temporal ordering in the analytical process to maintain the sequential nature of the observations of the epidemics.

2.2 Data Source

The data were derived from a time-series resource made publicly available by Salgotra et al. (2021). The source reports

epidemiological data daily for India, such as the number of people who are infected, recovered or died in the state or territory. A cumulative workbook from the most recent data file provided was chosen for analysis to avoid duplication from successive updates.

2.3 Data Preparation and Variable Construction

Data were checked for duplicate observations, missing data, errors in date format and errors in cumulative data. Geographic labels were standardized and observations were put in chronological order. Cumulative series with gaps in reports or inconsistencies were reconstructed, but with the same general temporal order and with non-decreasing cumulative numbers.

The main cumulative indicators of confirmed cases, recoveries, and mortality were kept. Consecutive differences of the respective cumulative series were used to obtain daily counts. The number of active cases was derived by subtracting cumulative recoveries and deaths from cumulative confirmed cases. Daily growth rate was calculated as the percentage change of the cumulative number of confirmed cases compared to the number of cases observed the day before. The recovery rate and case fatality rate were computed based on the number of cumulative confirmed cases. Daily series were also smoothed by calculating seven-day moving averages.

2.4 Descriptive and Growth-Trajectory Analysis

The following epidemic indicators were summarized using the numbers of valid observations, mean, standard deviation, median, minimum, and maximum. Confirmed cases, moving averages over 7 days, cumulative cases, and the percentage growth of cases were used to characterize epidemic growth. Monthly aggregation was performed to obtain the cumulative confirmed cases, number of cases added per month, mean daily incidence, peak daily incidence, mean daily growth, and percentage growth for each month. Changes in cumulative burden, daily incidence and growth trajectories were visualized using temporal plots.

2.5 Recovery Dynamics and Association Analysis

Cumulative recoveries, daily recoveries, recovery rate, active cases and case fatality rate were used to examine the recovery dynamics. Cumulative recoveries, mean daily recoveries, recovery rate, mean active burden, peak active burden, and case fatality rate monthly summaries were created. Daily recovery and mortality counts were plotted using 7-day moving averages. To test monotonic association between the variables, Spearman rank correlation was used: daily confirmed cases, daily recovered cases, daily deaths, active cases, daily growth rate, and recovery rate. Correlation coefficients were computed over pairs of available observations and were considered statistically significant at the 0.05 level of significance.

2.6 Temporal Forecasting

The daily confirmed cases series was taken as the forecasting series and was calculated using a seven-day moving average. Data were split chronologically into training and test sets at a ratio of 80% to 20% (without any randomization), thus preserving the temporal order of the data and ensuring that the future observations were not included in the model estimation process. Autoregressive integrated moving average (ARIMA) and Holt damped-trend exponential smoothing were used as the forecasting approaches. Only the training series were used to estimate the ARIMA specifications, and the Akaike information criterion (AIC) was used to determine model order. To get a directly comparable forecasting approach, Holt damped-trend estimation was performed on the same training period.

2.7 Forecast Evaluation

Both forecasting methods were tested only against observations in the held-out testing period. Mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) were used to quantify the error of prediction. The mean forecast bias was also computed to identify the direction and size of systematic forecast error. The smaller the value of MAE and RMSE, the smaller the absolute forecast error, and complementary metrics were included to describe the percentage-based error and forecast bias.

3. Results

3.1 Descriptive Epidemic Profile

There was considerable fluctuation in confirmed cases, recoveries, deaths and burden of disease in the analysed epidemic series during the course of this study. Table 1 shows that daily confirmed cases averaged $33,019.78 \pm 32,269.03$, with a median of 23,435 and a maximum of 279,896. Daily recoveries averaged $34,629.63 \pm 29,225.45$, while daily deaths averaged 470.21 ± 370.80 . Mean active cases were $403,594.91 \pm 300,706.53$, reaching a maximum of 1,021,053. The mean daily growth rate is 3.10%, the mean recovery rate is 73.88% and the mean fatality rate is 2.11%.

Table 1. Descriptive Statistics of Major Epidemic Indicators

Indicator	N	Mean	SD	Median	Minimum	Maximum
Daily confirmed cases	332	33,019.78	32,269.03	23,435.00	0.00	279,896.00
Daily recoveries	308	34,629.63	29,225.45	28,781.50	0.00	145,515.00
Daily deaths	332	470.21	370.80	404.50	0.00	2,003.00
Active cases	309	403,594.91	300,706.53	320,356.67	11,971.00	1,021,053.00
Daily growth rate (%)	332	3.10	4.09	2.12	0.00	26.49

Recovery rate (%)	309	73.88	23.07	78.86	10.30	97.77
Case fatality rate (%)	333	2.11	0.74	1.70	0.00	3.47

As of 19 February 2021, there were 10,963,131 cases, with 10,667,674 of them having recovered, as illustrated in Figure 1. The number of active cases peaked in the middle of the study period and then decreased, while the number of cumulative deaths rose to 156,111 at the end of the study period.

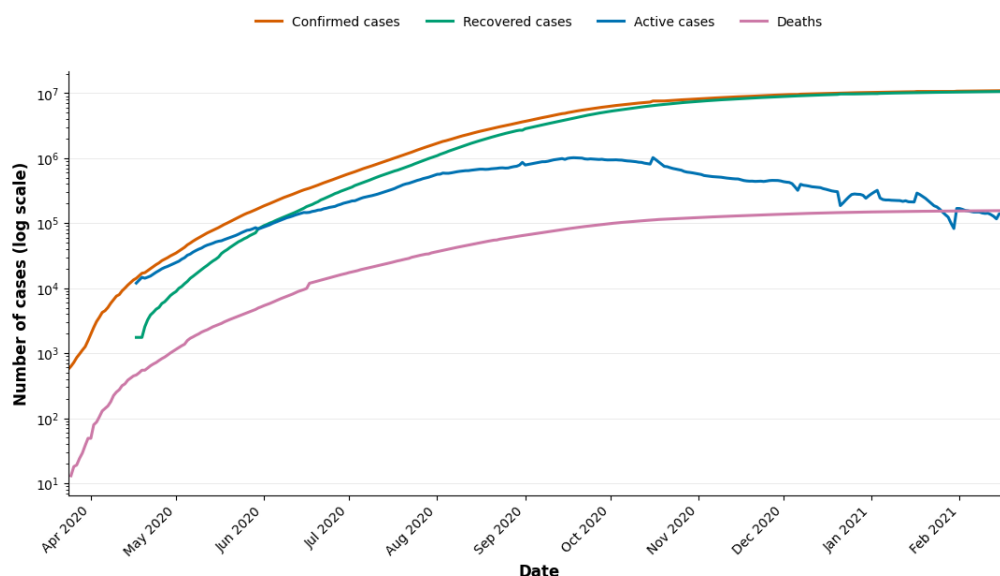


Figure 1. Temporal Evolution of Confirmed, Recovered, Active, and Death Cases During the Study Period

3.2 Epidemic Growth Trajectories

There was a sharp rise in the monthly incidence from the early epidemic period, followed by a decline in the latter months. As indicated in Table 2, the mean of daily reported cases rose from 142 in March 2020 to 34,807 in July, 63,948 in August and peaked in September with a mean of 86,817 cases per day. There were also 2,604,518 new cases in September. The mean daily incidence then dropped to 61,657 cases in October, 43,152 cases in November, 26,935 cases in December and 11,422 cases in February 2021. Growth in average daily increase dropped to 1.82% in September from 15.72% in March and 0.11% in February.

Table 2. Temporal Characteristics of Epidemic Growth Across the Study Period

Period	Cumulative confirmed	New cases during period	Mean daily cases	Peak daily cases	Mean daily growth (%)	Period growth (%)
March 2020	1,559	996	142	300	15.72	176.91
April 2020	33,050	31,491	1,050	2,000	10.88	1,575.96
May 2020	176,652	143,602	4,632	7,932	5.56	408.32
June 2020	559,842	383,190	12,773	20,090	3.92	202.77
July 2020	1,638,870	1,079,028	34,807	55,078	3.53	183.26
August 2020	3,621,245	1,982,375	63,948	78,761	2.59	113.52
September 2020	6,225,763	2,604,518	86,817	120,943	1.82	68.67
October 2020	8,137,119	1,911,356	61,657	279,896	0.87	28.90
November 2020	9,431,691	1,294,572	43,152	50,356	0.49	15.24
December 2020	10,266,674	834,983	26,935	115,872	0.27	8.49
January 2021	10,746,104	479,430	15,465	97,840	0.15	4.47
February 2021	10,963,131	217,027	11,422	32,582	0.11	1.91

The daily confirmed cases continued to rise steadily until mid-2020 and peaked at 97,263.14 for the seven-day moving average on 16 October 2020 before trending down (Figure 2A). The daily growth is highest during the initial observation period and decreases gradually and approaches near zero value in the later months, as shown in Figure 2B.

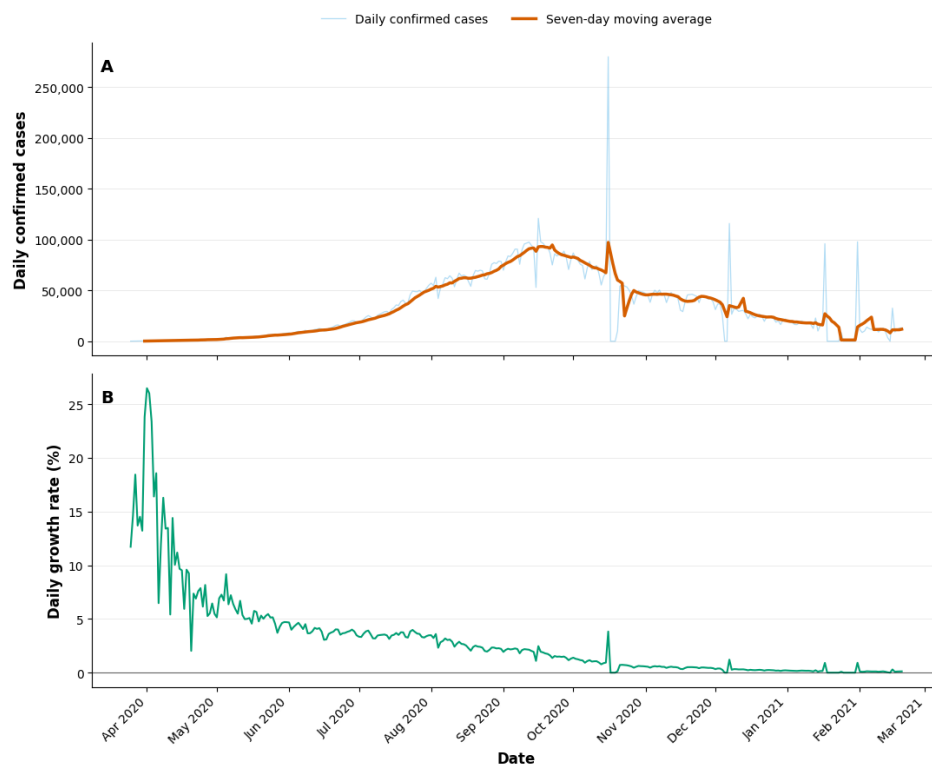


Figure 2. Temporal Patterns of Epidemic Growth During the Study Period. (A) Daily Confirmed Cases and Seven-Day Moving Average. (B) Daily Percentage Growth Rate

3.3 Recovery and Active-Case Dynamics

Signs of recovery varied significantly over the study period. Table 3 shows that cumulative recoveries increased from 8,325 in April 2020 to 5,187,825 in September and 10,667,674 in February 2021. During the same time, the recovery rate rose from 25.19% to 97.30%. Mean active cases reached 935,174 in September, while the maximum active burden of 1,021,053 cases was recorded during October. The mean active burden subsequently declined to 481,627 in November, 212,441 in January, and 144,095 in February. The case fatality rate is down from 3.25% in April to 1.42% in February.

Table 3. Monthly Recovery and Active Epidemic Burden Dynamics

Period	Cumulative recovered	Mean daily recoveries	Recovery rate (%)	Mean active cases	Peak active cases	Case fatality rate (%)
April 2020	8,325	506	25.19	17,547	23,651	3.25
May 2020	86,984	2,537	49.24	54,108	85,314	2.92
June 2020	334,822	8,261	59.81	144,343	208,127	3.02
July 2020	1,057,805	23,322	64.54	351,123	545,318	2.18
August 2020	2,694,367	52,792	74.40	668,709	862,409	1.78
September 2020	5,187,825	83,115	83.33	935,174	1,017,754	1.57
October 2020	7,432,829	72,419	91.34	806,076	1,021,053	1.49
November 2020	8,847,600	47,159	93.81	481,627	570,458	1.45
December 2020	9,854,253	32,473	95.98	323,446	435,603	1.45
January 2021	10,423,086	18,349	96.99	212,441	320,277	1.44
February 2021	10,667,674	12,873	97.30	144,095	168,197	1.42

The number of active cases peaked at 1021053 on 16 October 2020 and then began to fall to 139346 at the end of the study, with a recovery rate that rose to 97.30%. The seven-day average of daily recoveries peaked in the September–October period of 2020 and then fell, while the seven-day average of deaths stayed fairly low, as depicted in Figure 3B.

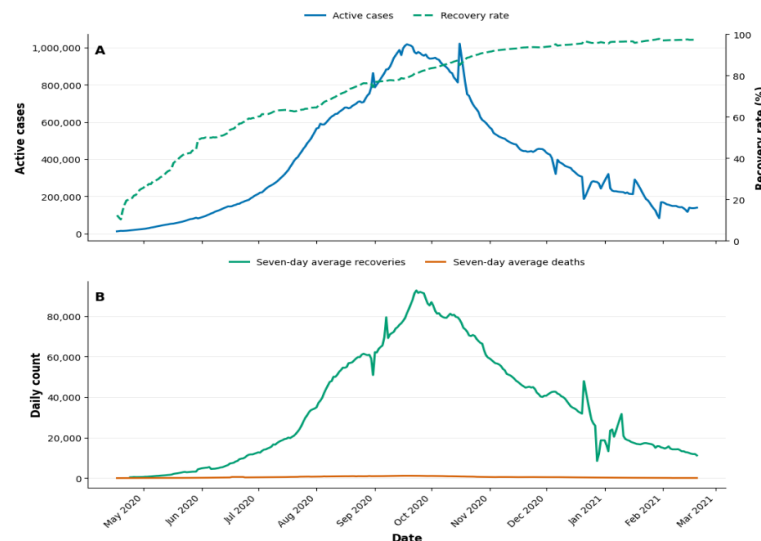


Figure 3. Recovery Dynamics and Active Epidemic Burden During the Study Period. (A) Temporal Changes in Active Cases and Recovery Rate. (B) Seven-Day Moving Averages of Daily Recoveries and Deaths

3.4 Correlation and Temporal Forecasting

There were consistent positive monotonic relationships for several epidemic indicators. Figure 4A revealed that daily recoveries were highly correlated with active cases (Spearman $\rho = 0.922$), followed by daily deaths with active cases (Spearman $\rho = 0.907$), daily confirmed cases with active cases (Spearman $\rho = 0.884$), daily confirmed cases with daily recoveries (Spearman $\rho = 0.799$) and daily confirmed cases with daily recoveries (Spearman $\rho = 0.799$). The greatest negative correlation was between recovery rate and daily growth rate ($\rho = -0.968$). The performance of the two models for time-series predictions varied. Table 4 shows that ARIMA(2,1,3) produced an MAE of 13,065.79 and RMSE of 14,900.78, compared with 7,540.36 and 9,346.85 for the Holt damped-trend model. MAPE was 313.00% for ARIMA and 219.54% for Holt, while mean forecast bias was 13,065.79 and 7,329.67, respectively.

Table 4. Comparative Performance of Temporal Forecasting Models

Model	MAE	RMSE	MAPE (%)	Mean bias
ARIMA(2, 1, 3)	13,065.79	14,900.78	313.00	13,065.79
Holt damped trend	7,540.36	9,346.85	219.54	7,329.67

As seen in Figure 4B, the forecast by the ARIMA model stayed around 29,000-30,000 cases for the entire test period, while the Holt forecast started at 28,800 cases and dropped to 20,700 cases. The observed test series had a mean of 16,635.20 cases and ranged from 1,231.92 to 28,099.57.

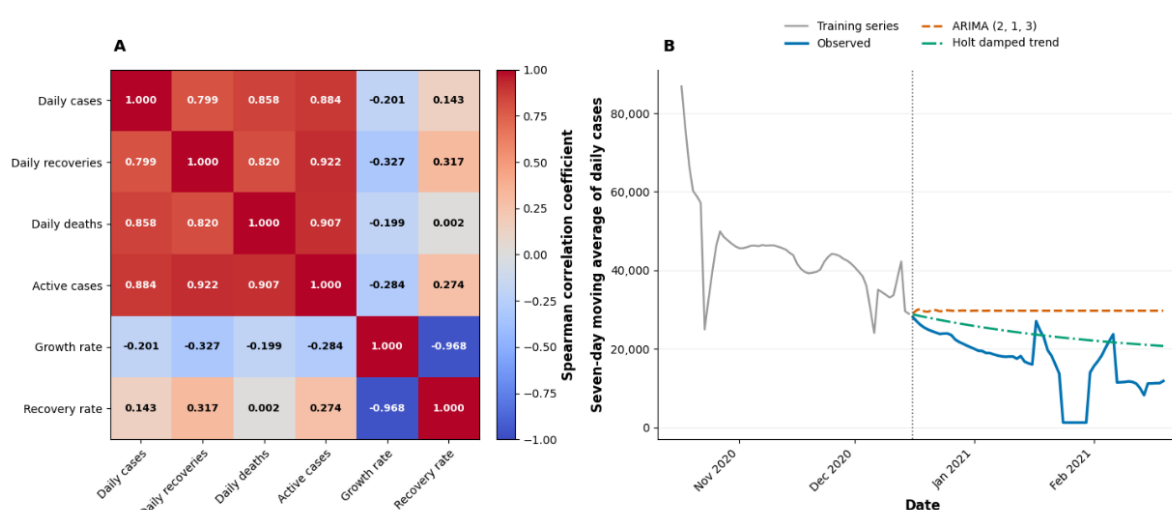


Figure 4. Correlation Structure and Temporal Forecasting of Epidemic Dynamics. (A) Spearman Correlation Matrix of Major Epidemic Indicators. (B) Observed and Forecasted Seven-Day Moving Average of Daily Confirmed Cases Using ARIMA and Holt Damped-Trend Models

4. Discussion

The epidemic curve showed a distinct shift from strong growth towards more and more moderate growth, and a reduction in the number of active disease cases. The seven-day moving average of mean daily incidence rose rapidly from mid-2020 onward and was the highest it has been each month in September, before falling. Meanwhile, the mean daily growth

slowed from 15.72% during March 2020 to 0.11% during February 2021. This difference between the cumulative burden and proportional growth suggests that there will likely be significant numbers of infections even when the relative rate of epidemic spread has slowed. The temporal change consequently reflects different stages of an increase in incidence, acceleration and then contraction in the spread, rather than a steady spread. This growth pattern was complemented by recovery dynamics. The recovery rate increased from 25.19% in April 2020 to 97.30% in February 2021, while active burden declined markedly after reaching its peak. Strong positive correlations between cases, recovered patients, fatalities and active cases indicated a similar trend as the cases progressed through the epidemic period. The pronounced inverse relationship between the growth rate and the recovery rate suggested a temporal relationship, i.e., the stronger the recovery, the weaker the epidemic growth. These associations are only a sign of co-movement and not a direct cause and effect. Forecasting results further showed model performance to be dependent upon the modulation of the epidemic series' structure. The MAE and RMSE values for Holt damped-trend forecasting were smaller than those of the ARIMA(2,1,3) model, and both models had positive forecast bias. The MAPE also showed high percentage errors, which suggests that MAPE is affected by low observed values during this testing period. The results of the forecasting models combined illustrate the challenges of extrapolating epidemic forecasts when the level and trend of the incidence are changing significantly.

The observed transition from epidemic growth to decay is consistent with the evidence of the COVID-19 propagation taking place in heterogeneous temporal phases. The propagation of epidemics is not adequately captured by a constant growth process, as was shown by Gross et al. (2020), who found significant spatiotemporal variation in the propagation of the pandemic. Rather, global trajectory analysis was able to find unique transmission features and shifts through the epidemic phases among infected populations (Loeffler-Wirth et al., 2020). Epidemic growth changes can also be a reflection of changes in population interactions. Kim et al. (2020) showed that a temporal rise in contacts could have a significant impact on the outbreak dynamics in South Korea. The spatial patterns in the early outbreak in China were also related to movement from Wuhan, showing the relationship between population movement and geographic distribution of the epidemic (Chen et al., 2020). The results offer a broader perspective on understanding variation over time in case trajectories, but were not directly used to model mobility or contact behavior.

The forecasting results are also in line with the widespread application of statistical time-series models throughout COVID-19. Benvenuto et al. (2020) showed that the ARIMA model can be used on an epidemic time series and could be considered a relatively "transparent" statistical forecasting method. Perone (2020) also used ARIMA to model the spread of the COVID-19 epidemic in Italy, as shown, demonstrating the ability of ARIMA to make forecasts based on the historical observation of an epidemic. Comparative studies have demonstrated that the predictive performance of models can be different during various epidemic phases and with different models. Kumar and Susan (2020) discussed the various time series models used for predicting COVID-19, and recommended model selection based on the desired characteristics of the observed trajectory. Watson et al. (2021) furthered the notion of epidemic forecasting by building a framework that combined machine learning, Bayesian inference and compartmental modelling. In the current analysis, lower forecast errors with Holt damped trend models further reinforce the general finding that the suitability of the model is not just a function of the complexity of the forecasting model.

The results agree with an integrated epidemic monitoring approach that uses cumulative cases in conjunction with daily incidence, growth rates, recovery, mortality and active burden. Using cumulative confirmed cases alone can mask significant changes in the intensity of the current epidemic, as the number of new cases may continue to rise despite a slowing increase in cases each day. Linking growth and recovery indicators can give a better picture of whether the burden of an epidemic is increasing, holding steady or decreasing. The 7-day moving average is a good way to see long-term temporal trends over short-term reporting fluctuations. Forecasts can also supplement these indicators by using near-term estimates, but should be analysed in conjunction with information on recent trajectory changes and with model errors. Chosen forecasting approaches for surveillance applications can also be justified using the comparison of alternative models on chronologically held-out observations.

A few limitations should be considered. The analysis was carried out using data from the ordinary time-series reporting; there can be slight deviations in day-by-day reporting. The study period was arbitrary and only represents the epidemic dynamics during this time frame. Also, the forecasting evaluation was limited to two known time-series methods. Future studies might involve a longer observation period and explore the state-level patterns as well as compare other forecasting techniques to determine the consistency of temporal patterns and predictive ability.

5. Conclusion

Throughout the observation period, there was a distinct trend of accelerated early growth followed by slower growth, with increasing recovery and decreasing active burden. Both absolute and proportional increases weakened over a period of time, with daily incidence rising until the middle of 2020 and the proportional increase weakening over time, demonstrating that absolute case counts and epidemic growth rate manifest different aspects of the dynamics of disease. A gradual increase in recovery over time resulted in a significant decline in active cases following the peak, and the recovery rate was near the upper limit of the range observed. The robust linkages between daily cases, recovered patients, and deaths, as well as the active burden, also illustrated the interconnected temporal dynamics of epidemic indicators. The forecasting results also indicate that the inclusion of growth trajectories, recovery dynamics, correlation patterns, and short-term forecasting in the model gives a more comprehensive picture of the evolution of the epidemic than does only cumulative cases.

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