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Data Science Methods to Develop Decision Support Systems for Real-time Monitoring of COVID-19 Outbreak

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Abstract

Data analysis and visualization are essential for exploring and communicating findings in medical research, especially in epidemiological surveillance. Data on COVID-19 diagnosed cases and mortality from crowdsourced website COVID-19 India Tracker, Census 2011, and Google Mobility reports has been used to develop a real-time analytics and monitoring system for the COVID-19 outbreak in India. We have developed a dashboard application for data visualization and analysis of several indicators to follow the SARS-CoV-2 epidemic using data science techniques. A district-level tool for basic epidemiological surveillance, in an interactive and user-friendly manner, which includes time trends, epidemic curves, and key epidemiological parameters such as growth rate, doubling time, and effective reproduction number, has been estimated. This demonstrates the application of data science methods and epidemiological techniques in public health decision-making while addressing the gap of timely and reliable decision-aiding tools.

Keywords: Public Health Data Science; COVID-19 Dashboard; Outbreak Monitoring; Decision Support System.

1. Introduction

As of May 15th, 2021, over 160 million confirmed coronavirus infections with over three million deaths across 192 countries were reported worldwide [1, 2]. According to the WHO COVID-19 situation update report on May 11th, 2021, India had over 22 million confirmed COVID-19 cases (3 million active cases) with close to 250,000 deaths [3, 4]. The government's decision of a nationwide lockdown during the initial phase of the epidemic and its sequential extension resulted in a significant reduction in the total number of COVID-19 cases in India. The effect of lockdown is also reflected by the decrease in the key epidemiological parameters of the COVID-19 outbreak in India [5–7]. However, this decrease was variable across different states and districts, which might call for a more cautious approach in the post-lockdown era [8]. The variation across different geographical and administrative regions also highlights the need for a more tailored approach based on individual clusters and the epidemic phase rather than taking a blanket approach.

The rapid spread of the COVID-19 pandemic has demanded collective action against coronavirus disease on an unprecedented scale [9–14]. Governments, organizations, institutions, and individuals came up with a vast array of innovations and technological advances in the field of infectious disease epidemiology and vaccine research [15–20]. Some of these innovations include innovative tools such as crowdsourced data generation, apps, dashboards, and

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tracker websites to monitor and track the COVID-19 outbreaks [1, 21–24]. Dashboards quickly became a popular tool to visualize and monitor the coronavirus disease spread and aid in decision-making and implementation of containment measures by tracking the critical epidemiological parameters and studying the transmission dynamics in real-time. A Google trend analysis shows that the keyword "COVID dashboard" quickly rose to peak popularity by the end of March 2020, with many such dashboards with varying degrees of granularity and interactivity developed for various purposes being available online.

1.1. Dashboards for Public Health Decision Making

From the general public to policymakers, government agencies, and even corporate research firms, many actively seek authentic information on COVID-19's impact on human lives—to stay updated and avoid misinformation-induced panic. Dashboards are tools that help in aggregating data from different sources in real-time and help in decision making. They are instruments for increasing transparency in decision-making and explaining policy decisions [25]. Another purpose of dashboards in COVID-19 has been to generate awareness about the case trends, track and monitor the epidemics while guiding them to corrective action in a timely fashion.

The applications and use of dashboards in the COVID-19 have been very diverse. These range from monitoring and mitigating preventive measures like social distancing and wearing masks to monitoring clinical trials. In the USA, dashboards were used to offer interactive visualization about the infection rates across different geospatial regions and the use of morgues in these areas. The authors used this tool for both aiding and increasing situational awareness as well as for capacity-building. It also helped the policy decision-makers and program managers to be better prepared for the epidemic and better utilize the available resources to the maximum benefit [26]. Dashboards also have been used in monitoring hospital infections and bed occupancy rates in the COVID-19 context as well as aiding in the monitoring of multiple drug and intervention trials [27]. In the Democratic Republic of Congo, a dashboard was created based on the variables collected from street passers about the perceived utility of preventive measures, actual practices, and adherence to mask. This was found to be an effective visual stimulation for daily monitoring [28]. The team behind a US dashboard (WATCHERS) argues the need to report trends at the municipality level in order to have a better understanding of the ground reality, which was lacking in the Centre for Disease Control and Prevention reports [29].

1.2. Indian Context

There have been several dashboards developed by the Indian government and various state governments [2, 30]. A few dashboards for India are developed by the academic institutes [31, 32] and by and volunteers [33, 34]. Table 1 shows a summary of some of the dashboards relating to COVID-19 in India. Apart from these, there are many other Github repositories, Tableau visualizations, and ArcGis pages that provide many insights on the transmission and impact of the COVID-19 epidemic. Crowdsourced initiatives like WhatsApp working groups and Telegram Folding groups that volunteer to maintain the tracking websites also play a crucial role. One such initiative is a tracking website (*covid19india.org*) curates count data published in state bulletins and official handles and provides an API for public use of the data. Many research papers, blog posts, visualizations and dashboards use these APIs for fetching the data. This is an excellent example of the benefits of information and communication technology for public benefit. Also, there have been instances where state governments realized the importance of dashboards for monitoring and tracking the COVID-19 epidemic is an illustration for the use of information technology in health governance [35].

Though many dashboards have been developed with varying levels of granularity for COVID-19, most of the dashboards fail to provide the crucial insights necessary to understand the transmission phenomenon. Barring a few, the majority of the dashboards are descriptive and do not provide additional information beyond case counts and deaths. Some dashboards which provided projections were far from the observed cases. One of the significant limitations of many such dashboards was the lack of domain knowledge. Thus, none of these dashboards have integrated the epidemiological aspects with social-geographical and macro-environmental aspects and have not seen the phenomenon with background susceptibility. Decision-making in public health could be viewed as a complex network of actors, agencies, and technologies with dynamic relationships. Lots of factors influence the decisionmaking in public health and these can be viewed at different levels (individual level i.e., patient, caregiver, clinician, program manager, decision-maker, policymaker, politician etc.; population-level i.e., socio-demographic variations, geospatial differences, etc.; infrastructure level i.e., health system capacity, health information infrastructure, digitalization of healthcare etc.; policy level i.e., health information use policy, public trust, vision, implementation etc.). This process is very complex and based on many interactions and relationships. Having good quality health information and robust health information systems could enhance the decision-making process. The current COVID-19 pandemic makes the case stronger for the urgent need for a more efficient epidemic tracking mechanism that can provide insights at the district level while also being scalable and reproducible.

Table 1. Summary of some of the COVID-19 Dashboards developed in the Indian context

No.	Region	Name	Organization	Туре	Update	Class	Granularity	Data Visualization	Geospatial Analysis	Data Source
1	India	WHO	Intl' Org.	Interactive	Daily	Strategic	National	Descriptive	Descriptive	-
2	India	MoHFW	Govt Org.	Static	Daily	Strategic	State	No.	No	MoHFW
3	India	ZOHO Analytics	Industry	Interactive	Daily	Analytic	State	Analytical	Descriptive	-
4	India	COVID19India.org	Crowd Sourced	Interactive	Realtime	Analytic	District	Analytical	Analytical	Crowd Soruced
5	India	Dataflix	Industry	Interactive	Daily	Analytic	State	Descriptive	Descriptive	MoHFW
6	India	Microsoft Bing	Industry	Interactive	Daily	Strategic	State	Analytical	Descriptive	Multiple
7	India	National Centre for Disease Control	Govt Org	Interactive	-	-	-	-	-	-
8	India	Pracriti - IIT Delhi	Academic Institution	Interactive	Daily	Analytic	District	Analytical	Descriptive	MoHFW
9	India	United Nations Major Group for Children and Youth	Industry	Static	Daily	Strategic	State	Analytical	Descriptive	MoHFW
10	India	Railway Enquiry	Industry	Static	Daily	Strategic	State	Descriptive	Descriptive	Multiple
11	India	National Remote Sensing Centre	Govt Org	Interactive	Daily	Strategic	State	Descriptive	Descriptive	MoHFW
12	India	Harvard School of Public Health	Academic Institution	Interactive	Daily	Strategic	State	Analytical	Descriptive	Multiple
13	India	FETP Network India - NIE, Chennai	Academic Institution	Interactive	Daily	Analytic	State	Analytical	Descriptive	Multiple
14	India	National Informatics Centre	Govt. Org	Interactive	Daily	Strategic	District	Yes	Descriptive	MoHFW
15	India	Chandeep	Individual	Interactive	Daily	Analytic	State	Analytical	Analytical	MoHFW
16	Nagaland	Govt of Nagaland	Govt Org	Interactive	Daily	Analytic	National	Analytical	No	IDSP, ICMR
17	Assam	Govt of Assam	Govt Org	Static	Daily	Strategic	District	No	No	Health Dept, Assam,
18	Karnataka	Govt of Karnataka	Govt Org	Interactive	Daily	Analytic	District	Yes	Descriptive	Health Dept, Karnataka
19	Odisha	Dept of Health and Family Welfare	Govt Org	Static	Daily	Strategic	District	Descriptive	Descriptive	Health Dept, Odisha
20	Punjab	Drona Maps	Industry	Interactive	Daily	Analytic	District	Analytical	Analytical	-
21	Bengaluru	Greater Bengaluru Municipal Corporation	Govt Org	Interactive	Daily	Analytic	Sub District	Analytical	Analytical	Health Dept BBMP
22	Delhi	Govt of Delhi	Govt Org	Static	Daily	Strategic	State	No	No	-
23	Punjab	Govt of Punjab	Govt Org	Interactive	Daily	Strategic	District	Descriptive	Descriptive	MoHFW
24	Puducherry	Department of Revenue & Disaster Management, Puducherry	Govt Org	Interactive	Daily	Strategic	State	Analytical	No	-
25	Kerala	Center for Development of Imaging Technology, Govt of Kerala	Govt Org	Interactive	Daily	Analytic	District	Analytical	Analytical	-

WHO – World Health Organization, MoHFW – Ministry of Health and Family Welfare, IIT – Indian Institute of Technology, FETP - Field Epidemiology Training Program, NIE – National Institute of Epidemiology, IDSP – Integrated Disease Surveillance Project, ICMR – Indian Council of Medical Research, BBMP - Bruhat Bengaluru Mahanagara Palike (Municipal Corporation, Bengaluru), Dept. – Department, Org - Organization

1.3. Objective

In this manuscript, we attempt to demonstrate the application of data analytics, data visualization, and epidemiology to develop an intuitive and interactive dashboard for real-time analytics and monitoring of the COVID-19 outbreak in India based on crowdsourced data.

2. Materials and Methods

2.1. Data Source

In India, confirmed cases of COVID-19 and deaths are reported to the Ministry of Health and Family Welfare (MoHFW), Government of India, through the national reporting network. The health authorities of the state simultaneously publish daily bulletins of the same. The crowdsourced database and website maintained at https://covid19india.org curates these bulletins and publishes this data into an application programming interface (API) available for public use. The API includes district-level, state-level, and national-level datasets. The downloadable dataset is updated regularly and contains the latest available public data on COVID-19 in India. The source of the data relating to district level population density was Census 2011, conducted by the Government of

India. A compilation of these figures is available from the Wikipedia page, which was scraped using the rvest package for scraping hypertext markup language (HTML) and eXtensible markup language (XML) tables. Additional data sources include the Google Mobility Trends dataset [36].

2.2. Variables Used for the Study

The variables used in the study are the daily caseload, including the confirmed cases, recovered, and deceased. These variables are provided by the API at https://covid19india.org. The population projections for 2020 for each state which were required to estimate indicators such as cases per million, deaths per million, and other relevant indicators such as for testing and vaccinations, were taken from the website of the Unique Identification Authority of India (UIDAI), which is the statutory body established under the Aadhaar Act, 2016 by the Govt of India [37]. Variables on COVID-19 vaccinations are sourced from the Open API provided by the COWIN portal, which is the official centralized portal for COVID-19 vaccinations in India. Additional variables reflecting the population dynamics, such as the mobility trends at the district level, were taken from the Google COVID-19 Community Mobility Report [36, 38], while variables providing details on contact tracing, testing, and hospitalizations for the state of Kerala were obtained from the Department of Health Services, Kerala website. These data are provided as part of the daily situation report in the form of a PDF (portable document format) which is then scraped for data using packages such as rvest [39].

2.3. Comparison of Epidemiological Parameters of the First and Second Wave

The epidemiological parameters that were estimated were growth rate, doubling time, and effective reproduction number. A detailed description of the methods on the estimation is provided elsewhere [7]. The end of the first wave and the start of the second wave has been defined as the day with the least number of cases after the peak of the first wave. The peak of the first wave was estimated to be 19th September 2020 (95% CI 18th September – 21st September). The valley was estimated to be 13th February 2021. The growth rate and doubling time to the peak of the first wave were compared with the growth rate and doubling time to the peak of the second wave.

2.4. Projections and Validation

For the purpose of the projections of the daily incident cases, we have made some empirical decisions based on some considerations. Taking into consideration the second wave of COVID-19 in India, we thought the best time to freeze the dataset would be 1st May 2021. This was done to include the most recent data but also to avoid any technical or erroneous entries in the recent past, which are usually rectified in a few days. We also decided the number of days for the projection of future incidence to be 15 as any projection beyond two weeks would mean a wide confidence interval and high error rate. Also, as the model is based on the regression of log incidence over time, it would be subject to overestimation as time progresses. We also decided on a 14-day moving average of the daily incident cases for modeling the future projections. For the epidemic simulation, we assumed that the branching process of the probability mass function follows a Poisson distribution.

Based on the considerations provided above, we then divided the dataset into two based on the date, 15th April 2021. The cases before 15th April 2021 were used to estimate the effective reproduction number by the time-dependent method developed by Wallinga and Teunis and improved by Cauchemez and colleagues [40, 41]. The effective reproduction number of 15th April 2021 was then extracted and provided as a hyperparameter for the epidemic simulation along with the distribution of the serial interval. As already described, we projected for each state the daily incident cases for the next 15 days and plotted against the observed 14-day moving average to check for the robustness of the effective reproduction number and the validity of the projections.

2.5. Implementation

The dashboard was developed using R, version 4.0.4, a free and open-source statistical software, and the RStudio, version 1.4.1106, an IDE interface. Key packages used for the dashboard development were the tidyverse packages, flexdashboard, and shiny. Graphing libraries like ggplot2 and plotly were used to create interactive and 3D data visualizations. Epidemiological analysis was done using the packages, incidence, projections, R₀, and EpiEstim. Packages rvest and fuzzyjoin were used to scrape sociodemographic information from the web and enable data linkage. The packages furr and future were used to optimize the code execution.

We used the package incidence to model the incidence and estimate growth rate and doubling time and package R0 to estimate the time-varying reproduction number (R_t) for different districts. The growth rate and doubling time were estimated by fitting an exponential model to the incidence data in the form of:

$$\log(y) = r \times t + b \tag{1}$$

where y is the incidence, t is the time (in days), and t is the growth rate while t is the intercept or origin. The doubling time is then estimated by dividing the natural logarithm of two with the growth rate of the epidemic i.e.

doubling time
$$(d) = \frac{\log(2)}{r}$$
 (2)

The package projections was used to simulate the epidemic outbreaks and project their respective trajectories based on the state-specific transmission parameters. Regression of log-incidence overtime was used to model the cumulative-incidence. Then we simulated 1000 probable epidemic outbreak trajectories and plotted the future daily cumulative incidence predictions based on the estimated time-dependent effective reproduction number. The time-dependent reproduction numbers were estimated using the method proposed by Wallinga & Teunis [41]. We substituted the generation time with the serial interval, which was chosen as a gamma distribution as it accommodates the underlying changing number of events. The mean and standard deviation for the serial interval approximations was 4.4 days and three days, respectively. The shape (number of events in a time-step) and scale (the reciprocal of event rate) of the distribution were 2.15 and 2.04, respectively.

2.6. Salient Features of the Dashboard

The components of the dashboard include the daily and cumulative estimates at the national, state, and district levels. These are both the incidence as well as mortality estimates such as deaths per million and case fatality rate, which was defined as the ratio between the number of deaths and the number of diagnosed cases. Other epidemiological parameters such as growth rate, doubling and halving time, as well as other indicators. The dashboard also incorporates other databases such as the sociodemographic information from the Census 2011 population estimates. Test positivity rate, tests per million are also estimated and presented in an intuitive fashion. This dashboard is intended to be used by public health stakeholders. A summary of the intended users and the mode of use has been provided in Table 2.

No. **Intended Users Intended Purpose** Mode **Updates** District-level program Evidence informed decision making; feedback on future 1 Interactive Dashboard Real-time managers improvements 2 Decision makers Dashboard Periodic Evidence informed decision making 3 Academia and researchers Discussion on methods; peer-review; academic discourse Dashboard + Methodology Real-time Citizen involvement, public discourse, media and 4 General public Website / Blog Periodic information professionals

Table 2. Summary of the intended users of the data analysis

2.7. Interactivity

The dashboard encourages the user to interact with the data and visualizations and offers a more immersive experience. The dashboard allows the user to select the state of interest and then specify the district that he/she would like to view. The dropdown menu allows for automatic updating based on the state selected. The scale of the axis i.e., linear or logarithmic, can also be specified by the user based on a check box beside the plot. This feature also allows the user to gain better insights into the transmission phenomenon. The three-dimensional graphs also add to the overall interactivity of the dashboard, allowing the user to zoom, pan, and rotate the 3D visualization. The plotly library also allows for the districts which are added as traces on the plot to be turned off or on without rendering the whole plot anew, thereby greatly enhancing the user experience.

2.8. Data Visualization

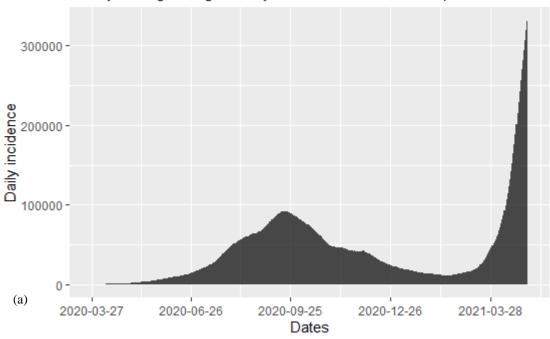
Data visualization such as epidemic curves, animated plots, time series plots, and 3D graphs have been used to visualize the data. Some of the relationships that were linear on 2D scatterplots show varied non-linear relationship across different geographical regions in the 3D graphs. Also, animated plots using the *gganimate* package allow for the static plots to come to life while increasing their interpretability.

3. Results

The full results of the study could be found as a standalone dashboard available at https://amchss-sctimst.shinyapps.io/covid_dashboard/. The shape of the epidemic curves not only suggests a classic case of a propagated epidemic but also points to the onset of the second wave of COVID-19 infections in India. Figure 1 shows the epidemic curve (daily and cumulative) for India, which clearly suggest the start of the second wave of COVID-19 infections in India, which is reflected in all the three plots, i.e., a spike in the daily new cases, the increase in cumulative cases and an increase in the R_t has also been noted.

The Epidemic Curve of COVID-19 in India

14-day moving average of daily incident cases until 30th April 2021



The Epidemic Curve of COVID-19 in India

14-day moving average of cumulative cases until 30th April 2021

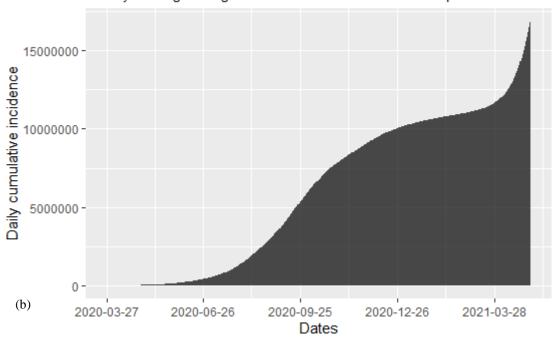


Figure 1. (a) The epidemic curve of daily new COVID-19 cases in India; (b) Cumulative incidence of COVID-19 in India

3.1. Epidemiological Parameters of the First and Second Wave

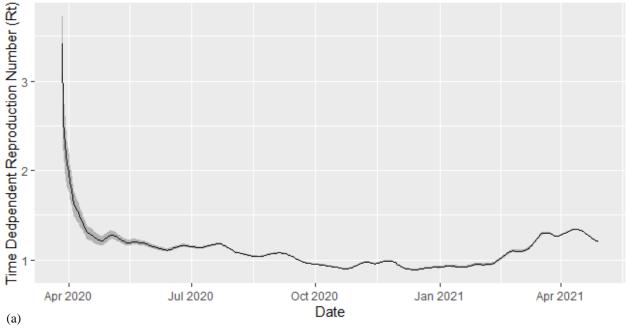
Almost all the states in India are experiencing a second wave of COVID-19 infections, as seen in the epidemic curve. The epidemic trajectories suggest a variation in the onset of the second wave among the states. Table 3 summarizes the key epidemiological parameters (growth rate, doubling time, peak of the first wave, and end of the first wave). It was found that the growth rate of the first wave (estimated until the peak of the first wave) is lower than that of the second wave. This was found to be true for almost all the states and union territories of India. Also, the doubling time that was estimated for the second wave was found to be lower than that of the first wave.

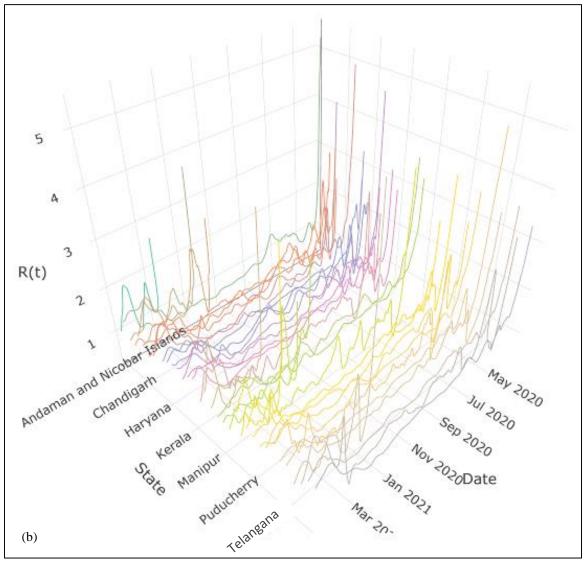
3.2. Estimation of the Time-dependent Reproduction Number (R_t)

The estimated time-dependent reproduction number (R_t) for India was above the threshold of one (Figure 2.a). Figure 2.b and 2.c illustrate the three-dimensional visualization of the time-dependent reproduction number across different states and districts of Maharashtra, respectively. The findings of the analysis suggest that the R(t) is well above the threshold of one in many states and requires closer monitoring. This also suggests that the second wave of COVID-19 infections in India is still in the exponential phase of the epidemic.

Table 3. The epidemiological indicators of the first wave and second wave across different states of India

No.	State	Peak of First Wave	Start of Second Wave	Growth Rate (First Wave)	Growth Rate (Second Wave)	Doubling Time (First Wave)	Doubling Time (Second Wave)
1	Andaman and Nicobar Islands	15-08-2020	30-01-2021	0.038	0.057	18.2	12.2
2	Andhra Pradesh	08-09-2020	20-02-2021	0.049	0.083	14.1	8.3
3	Arunachal Pradesh	02-10-2020	04-02-2021	0.039	0.172	17.6	4
4	Assam	10-09-2020	14-02-2021	0.056	0.075	12.5	9.3
5	Bihar	19-08-2020	12-03-2021	0.054	0.128	12.8	5.4
6	Chandigarh	20-09-2020	15-02-2021	0.032	0.047	22	14.7
7	Chhattisgarh	28-09-2020	04-03-2021	0.051	0.083	13.5	8.4
8	Delhi	14-11-2020	18-02-2021	0.019	0.084	35.8	8.2
9	Goa	22-09-2020	24-02-2021	0.044	0.06	15.9	11.5
10	Gujarat	04-12-2020	18-02-2021	0.014	0.059	50	11.7
11	Haryana	23-11-2020	14-02-2021	0.027	0.069	25.6	10.1
12	Himachal Pradesh	07-12-2020	24-02-2021	0.026	0.066	26.9	10.5
13	Jammu and Kashmir	21-09-2020	10-02-2021	0.031	0.052	22.3	13.4
14	Jharkhand	09-09-2020	24-02-2021	0.048	0.088	14.5	7.9
15	Karnataka	12-10-2020	24-02-2021	0.044	0.072	15.8	9.7
16	Kerala	13-10-2020	25-03-2021	0.041	0.08	17	8.6
17	Ladakh	16-11-2020	11-03-2021	0.019	0.114	36.2	6.1
18	Lakshadweep	13-02-2021	05-04-2021	0.061	0.153	11.4	4.5
19	Madhya Pradesh	24-09-2020	13-02-2021	0.026	0.062	26.7	11.2
20	Maharashtra	18-09-2020	11-02-2021	0.033	0.047	20.7	14.8
21	Manipur	23-10-2020	13-03-2021	0.026	0.095	27	7.3
22	Meghalaya	12-10-2020	27-02-2021	0.042	0.093	16.7	7.5
23	Mizoram	14-11-2020	13-03-2021	0.016	0.112	43	6.2
24	Nagaland	10-08-2020	28-02-2021	0.046	0.087	14.9	8
25	Odisha	27-09-2020	24-02-2021	0.047	0.079	14.6	8.8
26	Puducherry	02-10-2020	23-02-2021	0.045	0.067	15.3	10.3
27	Punjab	21-09-2020	28-01-2021	0.037	0.042	18.8	16.6
28	Rajasthan	01-12-2020	24-02-2021	0.019	0.084	36.6	8.3
29	Sikkim	27-09-2020	15-02-2021	0.031	0.066	22.4	10.6
30	Tamil Nadu	04-08-2020	25-02-2021	0.05	0.061	13.9	11.4
31	Telangana	06-09-2020	23-02-2021	0.04	0.065	17.5	10.6





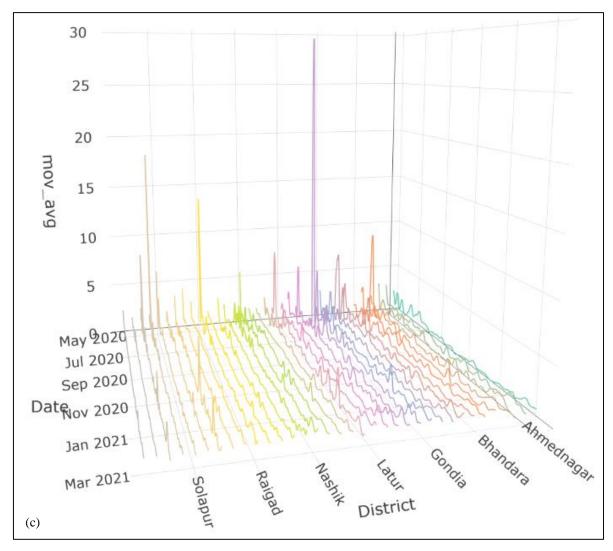


Figure 2. 2D and 3D visualization of the time-dependent reproduction numbers across different states and districts (Maharashtra for the purpose of illustration)

3.3. Projection of Future Daily Incidence for the Next 15 Days

The below figure (Figure 3) plots the projections of the future daily incidence (red-line) based on previous data (red-bars) against the observed daily incidence (blue-bars). It was found that the log-incidence overtime model performs well in predicting the future daily cases of COVID-19 in India. It was also found that since the estimation of projected cases (15th April 2021), there has been about 5% reduction in the R(t), which can be seen in the second panel of the below presented plot. Similar results were found in many of the states of India, especially where the second wave has started early. However, the model did not seem to perform well in states with fewer numbers of cases (daily incidence < 50 cases), especially in the north-eastern states.

4. Discussion

The current study demonstrates the applications of data science and epidemiologic techniques in tracking and monitoring COVID-19 outbreaks at the district level in India. The dashboard allows the use of scientific methodology and open-source technology to infer from the epidemiologic indicators in an intuitive manner. It not only allows timely information critical for decision making but also provides an interactive interface for the user. Some of the key inferences that can be made from the dashboard tracking COVID-19 epidemic in India are discussed below.

First, the incidence plots suggest the onset of the second wave of COVID-19 infections in India. The growth rate and doubling time have seen a steep increase when looking at the national context. Maharashtra saw a similar trend of increase in the number of cases as well as the key epidemiological parameters in the recent weeks. However, this second wave phenomenon has not yet been observed in all of the states. Also, within Maharashtra, there is a geographical variation across districts in terms of the current magnitude of the epidemic trajectory. This points to the fact that the phenomenon of COVID-19 transmission in India is not homogenous and needs to be looked at in greater detail.

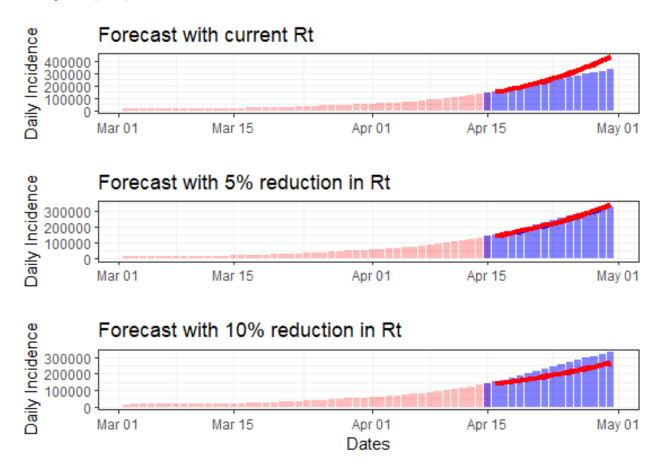


Figure 3. Projections of future daily incidence from 15th April 2021 to 30th April 2021. The projections are represented as a thick red line, while the observed cases are represented as blue columns on the x-axis. The light red columns on the x-axis represent the previous cases based on which the projections are estimated.

Second, the epidemic trajectory and rate of increase in epidemiological parameters like time-dependent reproduction number, growth rate, and doubling time during the first wave of the COVID-19 epidemic seen last year point to the "flattening of the curve" as suggested by many. In contrast, the rate of increase in the epidemiological parameters at the beginning of the second wave points to the intensity of infections, as seen clearly in the visualization part. Though it may suggest a grim future in terms of the impact of the second wave of COVID-19, this rate of increase may also be reflective of the responsive health system in terms of testing capacity and active case finding. The relationship between case incidences with population density across different districts also is interesting to note. Also, the association between the incidence and mortality estimates reveals that the relationship is not uniformly linear across the country. Different districts, based on their individual attributes, including sociodemographic variables, have an influence on this relationship.

Third, during the first wave, the capacity for testing and availability of tests have been low as compared to the present. The scaling of testing has been possible through the efforts of both governmental agencies and industry professionals. The regulations on price capping have ensured the affordability of COVID-19 testing in India. This has enabled in the improvement of data quality in the present time as compared to the first wave. The scaling of testing is inferred from the visualizations in the dashboard, but we can also see the relationship between the test positivity rate and the number of tests positives. This could mean that as we are increasing testing, the test positivity rate also has increased. Though the raw data required to make this inference is only available for the state of Kerala, this demonstrates the need to look at testing capacity and test positivity as a key performance indicator for the COVID-19 response. As data quality is fundamental to make meaningful decisions relating to public health, it is also important to acknowledge that health information is not immune from the political influences and strategic aspirations of the government.

The projections of the future incidence seem to provide robust estimates of daily incidence over a 15-day time period. The model performs well in estimating the future incidence in most states. The model overestimated the projections in states which saw an early second wave (E.g., Maharashtra, Uttar Pradesh, Chhattisgarh, Delhi). This could also be due to the relative reduction in R_t owing to the precautionary measures / public health interventions in these states. The model also performs well in all the southern states, such as Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, Telangana, and Puducherry. The model failed to provide robust estimates for the northeastern states as

well as some union territories such as Andaman and Nicobar Islands, Ladakh, and Lakshadweep. This may be due to the fact that there was a lack of adequate data and the daily incident cases were less than 50 per day. The model thus has many limitations as it does not take into account many important factors such as health system parameters, testing information, as well as vaccinations.

All of the aspects discussed above are dynamic in nature, i.e., as knowledge on COVID-19 is being updated every day there is an important need to review the situation on a frequent basis. Conventional methods in epidemiology and complex mathematical modeling approaches require high-quality data with little uncertainty, which might be difficult to come by in a low resource setting like India. The collective action of the community in providing support by curating the official information into an information exchange platform for public use is indeed a very welcoming and appreciative initiative. The collective action of various health departments, academic and research institutions, volunteers from the technology industry, and the general public made immense strides in advancing how health information is communicated.

The current dashboard has a lot of benefits over many existing dashboards available for India that have been discussed in the previous sections, but it also has a few limitations. We acknowledge the controversy about whether the data source is credible or not as a complex issue. Though there is a risk of undercounting new cases or deaths, our main data source has been used by many researchers for modeling COVID-19 in India. We also acknowledge that the application in its current form does not take into account the geospatial, genomic, climatic, or other factors relating to population dynamics and variation across the district. We hope to incorporate these variables in the subsequent versions of the dashboard. Some of the districts had to be excluded from the analysis due to some empirical constraints. Moreover, the analyses are not free from the biases linked to the source of information provided at https://covid19india.org. Hence, our estimates might not be an accurate representation of the on-ground reality.

4.1. The Road Ahead

Apart from using the study findings in teaching and academic discussion at various academic and research forums, the authors also intend to use them in the training of district-level program managers. The parent institute of the authors, Sree Chitra Tirunal Institute for Health Sciences and Technology, which is under the Department of Science and Technology, has been identified by the Government of India as the Regional Center of Excellence (RoCE) for training in the management of the COVID-19 epidemic in India. As part of the training of the district-level program managers in Kerala, the findings of the study would be shared as an interactive dashboard for aiding in decision-making. The feedback received would provide insights into user experience and help in the subsequent versions of the dashboard. This could in turn promote a data use culture and evidence-informed decision making. We also shared some of the findings of our study with the general public in the form of blog posts to invite citizen participation and public discussion.

5. Conclusion

The study demonstrates the usefulness of a data science approach coupled with robust epidemiological techniques in the application and development of an interactive and intuitive dashboard for aiding in decision making for COVID-19 in India. It is a proof of concept that aims to fill the gap by presenting a set of tools that are useful for near-real-time analysis and visualization of the epidemiological indicators for the monitoring and tracking of COVID-19 in India at the district level.

It is evident through this study, that appropriate data analysis and visualization has the potential to reveal hidden patterns and offer insights which are crucial for effective functioning of the routine public health surveillance systems. It has the potential to help with routine public health surveillance through watchful observation and designing public health interventions and corrective measures, while also aiding the program managers to understand the transmission dynamics in terms of disease trends and seasonality, which will help with better allocation, reallocation, and mobilization of precious resources. It could enable public health researchers to study the epidemiological trends and patterns of disease at different levels, such as individual, administrative, and regional. Additionally, such research initiatives can add value to data generated through the public health system and contribute to health system strengthening, promote data-use policy and culture, and lead to evidence-informed decision-making in public health. The engagement of key stakeholders like researchers, academia, and the general public is key to building trust in the decision-making process and effective implementation of intervention strategies. The dawn of the "infodemic" poses greater challenges in communicating research to build public trust. Traditional methods of communicating research may not be adequate warrant for newer and innovative ways to engage with the general public. Data-science methods can create opportunities for academic and public discourse, which not only improve the quality of evidence but also build public trust through citizen involvement and open-science.

6. Declarations

6.1. Author Contributions

Conceptualization, A.M., B.S., and R.G.; methodology, A.M., B.S., and R.G.; software, A.M.; validation, A.M., B.S., A.R., and G.S.; formal analysis, A.M.; investigation, A.M.; resources, A.M.; data curation, A.M.; writing—original draft preparation, A.M., B.S., R.G., and A.R.; writing—review and editing, A.M., G.S., and A.R.; visualization, A.M.; supervision, B.S. and R.G. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

Publicly available datasets were analyzed in this study. This data can be found here: https://data.covid19bharat.org/

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6.4. Institutional Review Board Statement

Not Applicable.

6.5. Informed Consent Statement

Not Applicable.

6.6. Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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