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## COVID-19 metrics across parliamentary constituencies and districts in India

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### ABSTRACT

In India, Parliamentary Constituencies (PCs) could serve as a regional unit of COVID-19 monitoring that facilitates evidence-based policy decisions. In this study, we presented the first estimates of COVID-19 cumulative cases and deaths per 100,000 population and the case fatality rate (CFR) between 7 January 2020 and 31 January 2021 across PCs and districts of India. We adopted a novel geographic information science-based methodology called crosswalk to estimate COVID-19 outcomes at the PC-level from district-level information. We found a substantial variation of COVID-19 burden within each state and across the country. Access to PC-level and district-level COVID-19 information can enhance both central and regional governmental accountability of safe reopening policies.

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### KEYWORDS

COVID-19; geographic precision; public policy; India



## 1. Introduction

As of 31 January 2021, more than 100 million COVID-19 cases and 2.2 million deaths have been reported spanning 219 countries and territories. Originated in China, COVID-19 affected southern Europe and the United States from its early stages. While developed countries are still enduring struggles, low- and middle-income countries (LMICs) overtook the global COVID-19 burden with high population density, lower levels of preparedness and a shortage of medical resources, including intensive care facilities. Indeed, India, Brazil and Mexico record one of the world's highest death tolls, following the United States. On 31 January, India reported 10.7 million confirmed cases and 157,000 deaths (see [Figure 1](#)), placing India as the country with second highest cases and the third most deaths globally ([Worldometers 2020](#)). However, the underlying burden is expected to be much higher than what is estimated, given the possible underdetection in India ([Worldometers 2020](#); [Zhang, Kim, and Subramanian 2020](#); [Dutta 2020](#)).

Not only has COVID-19 brought serious health consequences, but has also it incurred substantial economic crises in many countries regardless of the level of

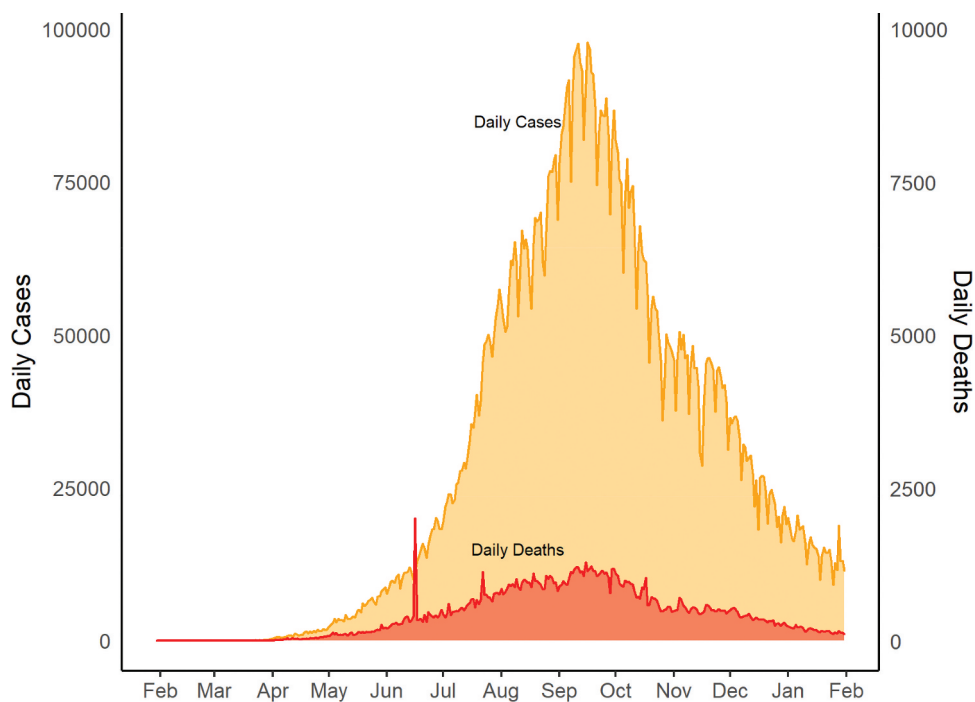
economic development. India was no exception. The 21-day national lockdown implemented in March 2020 contributed to containing the virus, yet it precipitated economic downturns. COVID-19-battered societies experienced massive job loss and disruption in supply chains. It has been estimated that up to 70–100 million more people may be pushed into dire poverty globally during the crisis, nearly half of whom are in South Asia ([World Bank 2020](#)). Now that the Government of India (GOI) has started to reopen the economy in a phased manner, the primary policy concern became mitigating the pandemic's economic impact while minimizing the life loss ([Srivastava et al. 2020](#); [Subramanian et al. 2020](#)).

Along with a focused effort to combat the spread of the virus at the national level, monitoring the spread of COVID-19 at the regional level is integral for effective policy design and implementation. In large countries like India, the burden of COVID-19 varies substantially across the country. For instance, the number of cases reported in the Maharashtra state reaches nearly 10-fold of any state in northeast India. In order to find the balance between the economic and health consequences of the virus, it is crucial to develop targeted interventions based on regional-level data ([Ankita et al. 2020](#)).

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**Figure 1.** Daily new COVID-19 cases and deaths for India as of 31 January 2021.

Parliamentary Constituencies (PCs) could serve as a regional unit of monitoring that facilitates evidence-based political discourse. And many public health studies in similar political units, such as congressional districts in the US, are widely available (deSouza and Subramanian 2020; Rolheiser, Cordes, and Subramanian 2018). The Members of Parliament (MPs) elected from 543 PCs across India represent at the Lok Sabha, the lower house equivalent of India, and serve two roles. First, they serve as lawmakers for the entire country. MPs sit in the Parliamentary Committees, Department Related Standing Committees and Public Accounts Committees that oversee budgets, plans and schemes. In the era of COVID-19, the Lok Sabha plays an integral role in designing legislation to help India counter COVID-19 and opening the national economy safely. Second, the MPs represent the interests of their constituencies, which is codified in the representation of MPs in District Planning Committees, District Development and Monitoring Committees and District Infrastructure Scheme Advisory (DISHA) Committees to monitor all centrally sponsored schemes. Therefore, the PCs play a critical link between the local, state and the government and offer opportunities for convergence between the administrative and political aspects of policy governance.

To guide evidence-based policymaking for COVID-19, we present a real-time monitoring framework of COVID-19 burden across PCs in India. Currently, India's COVID-

19 metrics representing the burden relative to the population size at the PC-level are not readily available. While the state-level counts are widely available, state-wise metrics lack efficiency as they cover a wide variety of population and regions. Given that 36 states and union territories cover 1.38 billion population, it is highly likely that the state-level metrics mask underlying geographic heterogeneity. While the metrics relative to the population size, such as cases and deaths per 100,000 and the case fatality rate (CFR), are used to make policy decisions such as reopening K-12 schools in other countries (Centers for Disease Control and Prevention 2020), such metrics have been particularly challenging to compute in India. The rapid population increase and geographic boundary changes complicated the linkage between the COVID-19 data and the population count.

To address the current lack of regional metrics, we used three COVID-19 metrics – cases per 100,000, deaths per 100,000 and the CFR – across the PCs and districts in India. Districts, the third tier of governance under the constitution of India, are the principal administrative unit in India (District Planning Committee 2007). While both districts and PCs are nested within each state, the boundaries do not align (The Delimitation Act 2002). PCs are typically a confluence of multiple districts or parts of districts. Among the 543 PCs and 736 districts, only 28 of them have identical boundaries. If PCs are central political geography, districts are a central unit of policy implementation exemplified by the nationwide

development programme called Aspirational Districts initiative. In the Aspirational Districts programme – as the name suggests – districts are the unit of monitoring and evaluation as well as development programme administration. As COVID-19 has surfaced as a pressing public health and development concern in India, the provision of a district-wide burden could further facilitate the implementation of health and economic policies.

In this paper, we showed the first set of cumulative cases and deaths per 100,000 residents and CFR between 7 January 2020 and 31 January 2021 across 543 PCs and 637 districts in India. We estimated the first-ever PC-level COVID-19 cumulative cases and deaths (per 100,000 residents) and computed the CFR from district-level data using a recently published geographic information science (GIS)-based methodology (Swaminathan et al. 2019; Blossom et al. 2019; Kim et al. 2019). Using the methods introduced in this paper, we published a real-time monitoring dashboard of COVID-19 metrics to be further utilized for the monitoring of COVID-19 and PC- and district-level risk assessment (available at <https://geographicinsights.iq.harvard.edu/IndiaVaccine>). Of note, the India COVID-19 API have stopped updating their case and death metrics in November, 2021. Furthermore, such a monitoring framework could be applied to track other domains of public health.

## 2. Methods

### 2.1 Data sources

#### *District-level COVID-19 dataset*

We obtained the number of COVID-19 cases and deaths across the districts in India from Covid19India (2020). Covid19India (<https://www.covid19india.org/>) is a crowdsourced platform that collects four COVID-19 metrics on a daily basis – the number of confirmed, active, recovered and deceased cases. This platform obtained the data from state bulletins and the official state COVID-19 reports, in which most of the states publish district-wise statistics. However, the data from seven states of the Andaman and Nicobar Islands, Goa, Assam, Sikkim, Telangana, Manipur and the National Capital Territory (NCT) of Delhi were either not formed at district-level or outdated. Due to data quality concern, we only report state-level counts instead of district-level counts in those states. In addition, the data were unavailable in Noklak in Nagaland and Saitual from Mizoram.

Lastly, the cases that were not assigned to any districts were excluded from our analysis. After excluding the districts where the data were not available, we had COVID-19 cumulative cases and deaths for 637 reporting units (including 630 districts and 7 states/UT, referred as 637 districts).

#### *District boundary shapefile for COVID-19, 2020*

Since no up-to-date official district shapefile was available, we created a district shapefile using the existing district shapefiles and additional governmental resources, considering the district boundary changes over time. Three data sources were used: The first was the India district shapefile of Census 2011, downloaded from the Community Created Maps of India (CCMA) (Data{Meet}. 2019). This shapefile contained the boundaries of 640 districts as of 2011. The second source was the Bharat Maps (2020) published by the Ministry of Electronics and Information Technology of the Government of India, a multi-layer GIS platform with administrative boundaries in 2020. The last was notification documents of district boundary change by the Reserve Bank of India (2020). We obtained the information on new district formation, including the formation date, erstwhile district and sub-districts.

We used the India district shapefile of Census 2011 as a base map and edited its boundaries using the Bharat Maps as a reference for district borders for districts in 2020. Georeferencing and the edit functions in ArcGIS Pro 2.6.0. were used to create a new district boundary on a scale smaller than 1:1,000,000. For the Andaman and Nicobar Islands, Goa, Assam, Sikkim, Telangana, Manipur and the National Capital Territory (NCT) of Delhi where the district-level COVID-19 data were not available, we dissolved the district boundaries into the states. Therefore, the COVID-19 metrics in these seven states were presented at the state-level metrics rather than the district-level. Overall, 637 districts including those dissolved into states were identified in our district shapefile.

#### *PC Boundary shapefile*

We downloaded the PC boundary using Community Created Maps of India (CCMA) (2019). The shapefile contained 543 polygons of PCs in India and was last modified and published in April 2019. Unlike districts, PC boundaries have not been altered since the Delimitation Act of 2002. To validate the accuracy of the shapefile, we compared the PC boundary with Bharat Maps (2020) and made minor adjustment accordingly.

### District and PC population count

We used gridded population count data published by the WorldPop to estimate the population across districts and PCs in 2020 (WorldPop 2017). The India 100 m Population Data provides population estimates at 100 m × 100 m spatial resolution, which were developed using demographic information, land cover remote sensing imagery analysis and dasymetric modelling. The population estimate by the WorldPop was granular enough to model the population across districts and PCs, which also accounted for the heterogeneity of population density between urban and rural areas (Blossom et al. 2019).

### 2.2 Methods

We used the crosswalk method, a type of dasymetric mapping technique, to derive PC-wise COVID-19 estimates from district-level data (Rockli et al. 2019; Swaminathan et al. 2019) (see Figure 2). In essence, if a PC spans across multiple districts, we computed the average of district indicators weighted using the population proportion in each PC, assuming that the COVID-19 metrics were uniformly distributed across the population in one

district. For example, if a single PC spans across districts A and B, we first divided this PC segment into each district as segments A and B, respectively. If segment A contained 40% of the population of district A and segment B contained 60% of district B population, the total number of cases was calculated by summing up the total cases in two districts weighted by the proportion of the population (Swaminathan et al. 2019). Similarly, we summed the population count across 100 m × 100 m pixels using the WorldPop population raster data within each segment. This analysis was conducted using the ArcGIS Pro 2.6.0.

The accuracy of crosswalk is validated in a recent study by Kim et al (2019). The authors compared the prevalence of child malnutrition at PC level between two methods – crosswalk and precision-weighted estimates from direct linkage of primary sampling units (PSUs) to PCs using GPS data. The results showed little difference between two methods. Correlations between estimates produced by the two methodologies are 0.97 and 0.94 for stunting and low birth weight indicators. Given that COVID-19 data are not available for smaller geographic units similar to PSUs, we adopted a crosswalk method which requires district-level data to present for estimation.

1. Calculate district area (dist\_area): perform 'Calculate Geometry' function on the district shapefile, using the Kalianpur 1975/India Zone IIa (EPSG: 24379) coordinate system
2. Calculate district population (dist\_pop): perform 'zonal statistics' command using district shapefile as the 'zone' and the WoldPop2020 as the data raster
3. Link each segment contained both district ID and PC ID of the overlapping over; perform 'intersect' command to district and PC shapefile, create a new shapefile called Dist\_PC\_intersect. In total, there are 3734 segments
4. Calculate segment area (seg\_area) and segment population (seg\_pop) following step 1 and 2
5. Calculate percentage of district population (Pct\_pop) in each segment by segment population dividing district population
6. Calculate percentage of district area (Pct\_area) in each segment by segment area dividing district area. Remove segments that were less than a hundredth of a percent of the original district area. Those extremely small areas are created because of the slight boundary inaccuracies between district and PC shapefiles. A hundredth is chosen as a conservative threshold. There remain 3,548 segments in the intersected shapefile
7. Calculate number of confirmed and death cases in each segment: multiply number of confirmed and death cases in the district by percentage of district population in the given segment
8. Calculate PC level confirmed and death cases, and population estimate: aggregated segment level confirmed and death cases, and population by PC ID
9. Calculate PC level confirmed cases per 100,000, deaths per 100,000 and CFR

**Figure 2.** Flow chart of how to use the crosswalk to derive COVID-19 cumulative cases and deaths per 100,000 population and CFR from district-level outcomes.

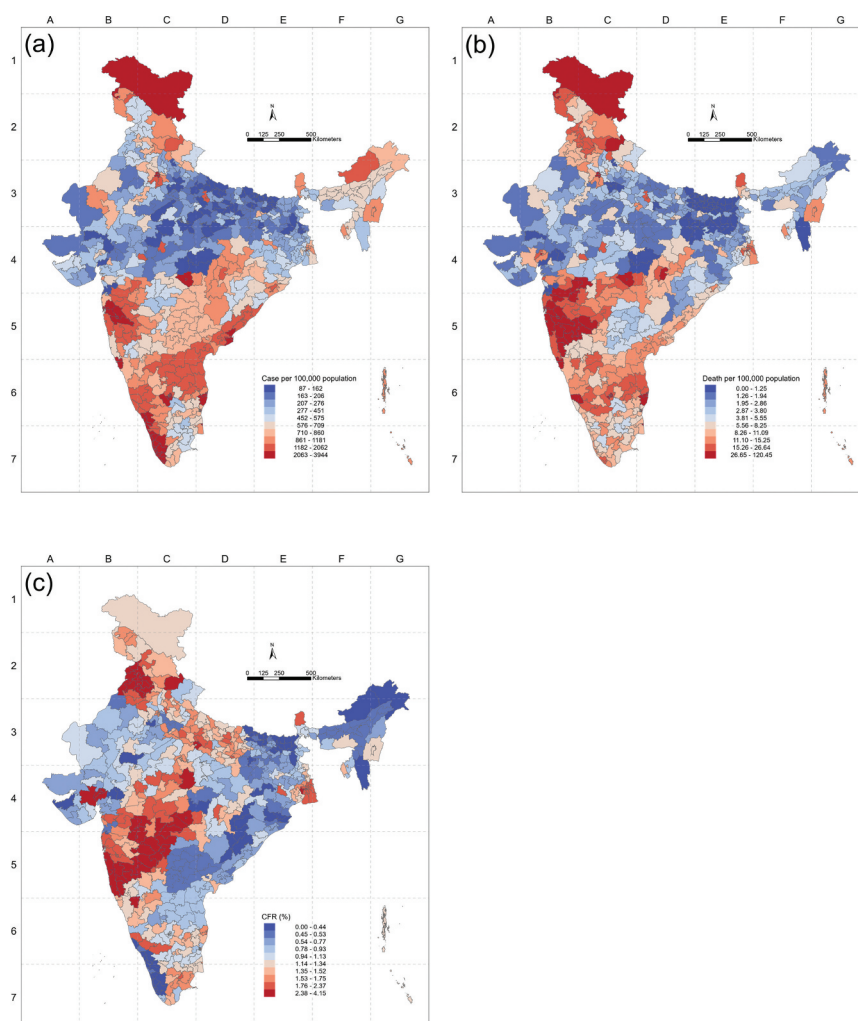
## 2.3 Analysis

We considered three COVID-19 metrics: cases per 100,000, deaths per 100,000 and the CFR. Absolute counts on cases and deaths are also available in supplementary materials. All metrics were cumulative. We computed cases per 100,000 by dividing the estimated PC-wise count of confirmed cases by the population count of the PC and multiplying by 100,000. Similarly, deaths per 100,000 were calculated as the number of deaths divided by the population, multiplied by 100,000. CFR was calculated by dividing the number of cases by the number of deaths, multiplied by 100. We classified the PCs into deciles from the highest (i.e. 10th decile) to the lowest burden. We also presented descriptive statistics across all PCs nationally and within each state. We adopted

boxplots to show the interquartile range (IQR) of metrics within the states for a visual representation of the COVID-19 burden across India. This analysis was conducted using R version 4.0.2.

## 3. Results

The total number of PCs after excluding the districts without appropriate data was 543. In the following section, we present COVID-19 cases per 100,000, deaths per 100,000 and the case fatality rate across 543 PCs as of 31 January 2021. All metrics are cumulative. The same metrics across 637 districts of India are shown in the Appendix. We also build a web-based dashboard to illustrate spatiotemporal dynamic of COVID-19 cases/death count (Kumar, Zhang, and Subramanian 2020).



**Figure 3.** COVID-19 metrics across PCs in India. (a) Cases per 100,000; (b) Deaths per 100,000; and (c) CFR (%). Note: The colour gradient from darkest blue to darkest red represents the decile distribution from the lowest to the highest on the cases/deaths per 100,000 population.

### 3.1 Distribution of COVID-19 cumulative cases per capita

Cumulative cases per 100,000 population ranged from 87 to 3,943 with a mean of 831 per 100,000. The states with PCs ranked in the top decile with the highest number of cumulative cases per capita are Kerala (16 PCs/total PCs: 20), Maharashtra (15 PCs/total PCs: 48), Delhi (7 PCs/total PCs: 7), Tamil Nadu (5 PCs/total PCs: 39) and Karnataka (4 PCs/total PCs: 28). The states with PCs ranked in the bottom decile were Uttar Pradesh (23 PCs/total PCs: 80), Bihar (14 PCs/total PCs: 40), Madhya Pradesh (9 PCs/total PCs: 29) and Gujarat (4 PCs/total PCs: 26) (Figure 3a).

### 3.2 Distribution of COVID-19 cumulative deaths per capita

Cumulative deaths per 100,000 population varied between 0 and 120 with a mean of 11.7. The states with PCs ranked in the top decile with the highest number of cumulative deaths per capita were Maharashtra (28 PCs/total PCs: 48), Delhi (7 PCs/total PCs: 7), Tamil Nadu (5 PCs/total PCs: 39) and Karnataka (4 PCs/total PCs: 28). The states with PCs ranked in the bottom decile were Bihar (33 PCs/total PCs: 40), Jharkhand (6 PCs/total PCs: 14), Gujarat (5 PCs/total PCs: 26) and Uttar Pradesh (5 PCs/total PCs: 80) (Figure 3b).

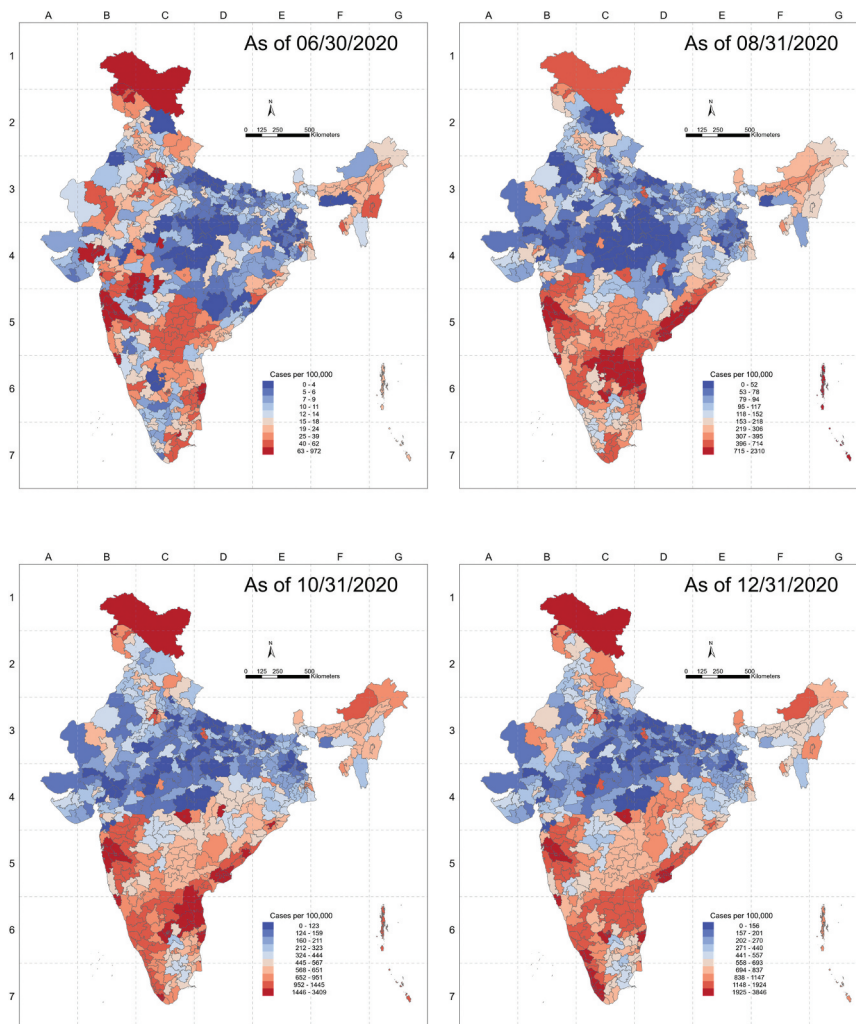
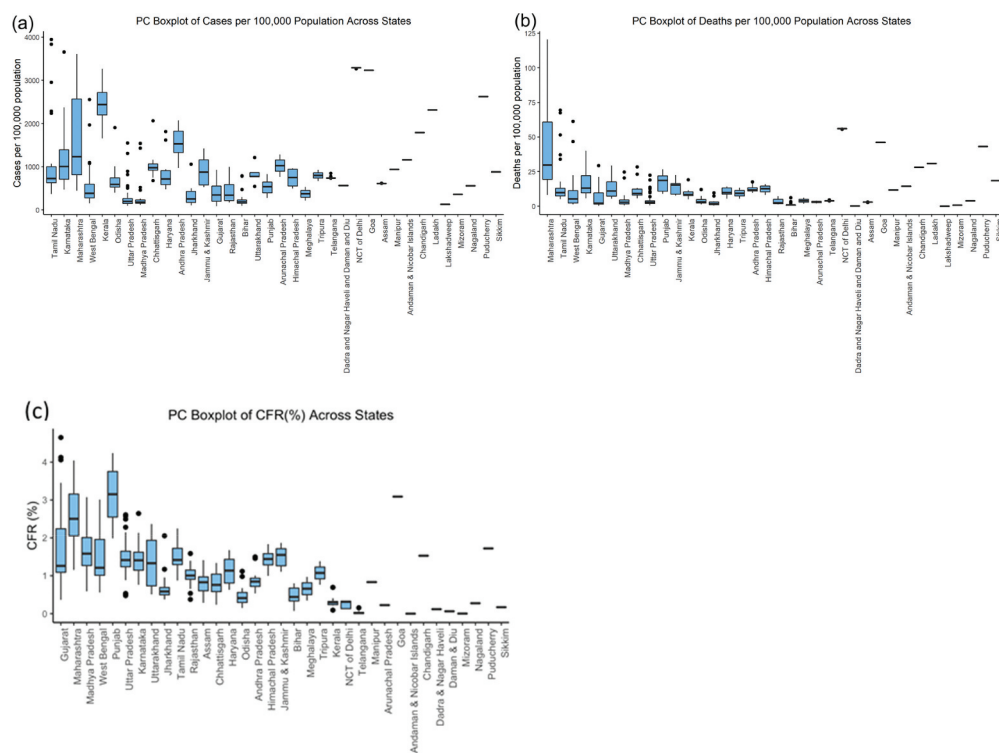


Figure 4. Cumulative COVID-19 cases across PCs in India as of different time range.



**Figure 5.** Boxplot of COVID-19 for PCs within states for (a) cumulative cases per 100,000, (b) cumulative deaths per 100,000 residents and (c) CFR (%).

### 3.3 Distribution of COVID-19 case fatality rate

The CFR ranged from 0% to 4.14% with a mean of 1.27% at PC level. The states with PCs ranked in the top decile with the highest CFR were Maharashtra (29 PCs/total PCs: 48), Punjab (12 PCs/total PCs: 13), Gujarat (5 PCs/total PCs: 26) and West Bengal (3 PCs/total PCs: 42). The states with PCs ranked in the bottom decile were Bihar (17 PCs/total PCs: 40), Kerala (16 PCs/total PCs: 20) and Odisha (8 PCs/total PCs: 21) (Figure 3c).

### 3.4 Spatiotemporal dynamics of COVID-19

COVID-19 metrics show significant variability across time and states. For example, as of 30 June, only 5 out of 20 PCs in Kerala ranked in the top 5 deciles for cumulative cases per 100,000, while as of 31 December 2020, all PCs in Kerala ranked in the top 5 deciles, and 14 PCs ranked in the top decile. In the meantime, Gujarat and Tamil Nadu's situations have been alleviated, with fewer PCs ranked in the top 5 deciles for cumulative cases per 100,000 (Figure 4). To illustrate the temporal dynamics at the state and national levels, we build an interactive web-based dashboard on COVID-19 metrics at <https://>

[geographicinsights.iq.harvard.edu/IndiaVaccine](https://geographicinsights.iq.harvard.edu/IndiaVaccine). Of note, the India COVID-19 API have stopped updating their case and death metrics in November, 2021.

### 3.5 Variability across districts and PCs by state

We found a substantial variation in cases and deaths per 100,000 population across PCs and districts within states (Figure 5(a-c)). For example, Karnataka and Tamil Nadu had the highest cumulative cases per 100,000 population in India. Tamil Nadu had the highest variance for cases per population in India (min: 369, max: 3,943, mean: 1,019,  $n = 39$ ) among all states. Comparing the variance across the districts and PCs, we observed a larger variation in COVID-19 outcomes across PCs than districts. The standard deviation of cases per population at the PC-level was 832, while for districts, it was 713. Similarly, the standard deviation of deaths per capita across PCs was 18, while across districts, it was 11.

## 4. Discussion

In this study, we showed a COVID-19 monitoring framework across 543 PCs and 637 districts in India. As we aimed to present the first set of COVID-19 metrics at the

PC-level, the results presented in this paper can guide policy directions. First, we found a substantial variation across the PCs and districts even within each state. For instance, the range of PC-wise cases per 100,000 varied from 369 to 3943 in Tamil Nadu, the state with the highest COVID-19 burden as of 31 January 2020, while district wise, the range varied from 333 to 4464. Such wide variation across the PCs and districts within the states showed that targeted interventions at geographic levels below the state are needed. Second, we found different geographic distribution between the three metrics, which suggests that all three metrics should be considered in resource allocation and reopening decisions. For instance, the medians PC-wise COVID-19 cases per 100,000 were similar between Andhra Pradesh and Maharashtra (1526 vs. 1232), and deaths per 100,000 were much lower in Andhra Pradesh than in Maharashtra (12 vs. 30). While more information should be examined, this could suggest that more health care resources such as ICU facilities are needed in Maharashtra.

While this is the first study to show three COVID-19 metrics at the PC level in India, there exist limitations that stem from the data sources used for analysis and the estimation method. First, our district-level data source ([covid19india.org](https://covid19india.org)) is a non-official, open-source website, by which the data input could be inaccurate, and could not be confirmed or validated. Nevertheless, we chose this data source for two reasons. First, this was the only choice available for COVID-19 data at the district-level in India. Second, previous studies have shown that such crowdsourced data agrees well with official data and is more up-to-date compared to official information (Weixing, Kim, and Subramanian 2020). The second limitation originates from the crosswalk method used to derive PC-level estimates. This method assumes that the COVID-19 cases and deaths were uniformly distributed within the district and are proportional to population. Although it is impossible to validate this assumption, we adopted population count estimates that are granular enough to exhibit heterogeneity between urban and rural areas (Blossom et al. 2019).

Despite such limitation, this study showed that the application of GIS could further the utility of COVID-19 metrics for policymakers as well as the constituents. While the method adopted in this study has been introduced elsewhere, we use this method to present COVID-19 metrics across policy-relevant units. PCs are important geography as a major part of the resource allocation decisions, and guidance is still provided by the national government through centrally sponsored schemes, such as the National Health Mission and Prime Ministers Jan Arogya Yojana.

Access to PC-level COVID-19 data can help MPs determine which bills to push for, effectively communicate the scale of the crisis to their constituents and design social distancing policies that are needed to be enforced. Such data can also allow MPs to learn from the experience of other PCs. Equally important, as COVID-19 is a time-sensitive and highly noticed agenda, COVID-19 metrics at the PC-level could help its constituents to engage with their MPs and evaluate the performance of the central government.

In addition, districts could serve as a central geographical unit for the implementation of COVID-19 policies. Districts in India have a dedicated funding mechanism based on State Finance Commission's recommendations under Article 243I, which recommends principles for sharing of revenues within each state. Through such mechanisms, having COVID-19 estimates at the district level can facilitate such administrative functions and guide hotspots targeting and the allocation of critical resources. Therefore, considering the PC- and district-wise burden of COVID-19 simultaneously could guide policies from design to implementation.

In conclusion, we established a national monitoring system to track COVID-19 statistics across PCs and districts in India. We aimed to present the first set of metrics of COVID-19 at these geographic scales and provide a methodological flow chart for such a monitoring scheme. This study could enhance the geographic precision of COVID-19 data in India for evidence-based assessment of safe reopening policies.

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## Author Contributions

All authors have read and approved the manuscript.

Conceptualization and design (SVS, RS and RK); data acquisition and analysis (WW and WZ); data interpretation (WW, JK, WZ, RK, RS and SVS); drafting of the manuscript (WW, JK and PD); critical revisions to manuscript (WZ, RK, RS and SVS); and overall supervision (SVS).

## Data Availability Statement

The COVID-19 crowdsourced data are accessible at [covid19india.org](https://covid19india.org).

## Disclosure statement

No potential conflict of interest was reported by the authors.

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