The spatio-temporal trajectory of COVID-19 in India: insight into past pandemics and future recommendations

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Pandemics have a high socio-economic impact on countries. Singapore and Taiwan, which had pandemic strategies in place, fared much better than almost all other countries in the world during the recent COVID-19 pandemic. In a massive country like India, the coronavirus (COVID-19) has infected millions of people. While studies have estimated the rate of transmission and vulnerability zones, there is still a pressing need to understand the spatio-temporal progression of various pandemics across the population. Here, we review the spread of pandemics in India and identify states with a high probability of being initial hotspots. It was found that pandemics tend to follow a similar transmission route in India. For the COVID-19 pandemic, a spatial link has been established between seasons and disease progression. For instance, districts are marked where a sudden increase in cases (as high as 800%) was observed during monsoon (i.e. rainy season). Following the spatio-temporal trajectory of COVID-19 in India, we found that in post-monsoon, northern regions with hilly terrain witnessed the highest increase in the number of cases. Identifying areas on the trajectory of pandemics will help us better prepare for an outbreak more effectively in the future.

Keywords: Hotspots, pandemics, transmission route, seasons, spatio-temporal trajectory.

THE world at large is facing more intense disease outbreaks in recent times. However, countries such as Singapore and Taiwan have set an example by implementing better response strategies during COVID-19 (ref. 1). Earlier, the Spanish flu was considered as the deadliest pandemic, but with COVID-19 the number of people and countries affected has far exceeded the Spanish flu numbers. In India alone, millions of people have been infected with COVID-19 (ref. 2), and numerous studies have been conducted to determine the transmission rate and risk zones to deal with the situation[3,4]. Surprisingly, however, there appear to be some striking similarities between the two pandemics, separated by a century[5]. Possibly there are some relevant lessons to be learnt from these pandemics. The two diseases have been compared in terms of the magnitude of infection and epidemiological characteristics in the United Kingdom[6]. In USA, a New York city-based study has found close relationship between mortality rate of COVID-19 and Spanish flu with an indecent rate of 202.08 and 287.12 deaths per 100,000 persons every month respectively[7].

As a developing nation, India has experienced several epidemics and pandemics over time. It is crucial to study the trend of pandemics in India to understand disease transmission trajectories. It has been observed that hotspots of epidemics emerge from specific regions. For example, five states; viz. Maharashtra (MH), Gujarat (GJ), Rajasthan (RJ), Delhi (DL) and Tamil Nadu (TN) have been among the main hotspots of COVID-19, accounting for more than 70% of India's confirmed cases as on 31 May 2020 (Figure 1). Moreover, data from the National Centre for Disease Control (NCDC), Delhi show that these are the same states that consistently accounted for the bulk of swine flu cases or seasonal influenza (H1N1) since 2010 (ref. 8). The year 2015 witnessed the most H1N1 cases (42,592), and MH, RJ, GJ, DL and Karnataka (KA) accounted for 71% of the total cases[8]. Furthermore, in 2017 and 2018, these same five states reported 60% and 59% of the confirmed infections respectively[8]. Again, in 2019, the aforementioned five states made up 62% of the total H1N1 cases. In case of COVID-19, these five states find a mention in the list of top 10 most affected as of 31 August 2020. The present study aims to provide policy recommendations to ensure a more calibrated and tailor-made approach to combat future pandemics in a more targeted manner. Notably, the most affected states like MH, GJ and KA also contribute maximum to India's gross domestic product (GDP). Therefore, it is imperative to take precautionary measures in these states in case of future outbreaks. It is worth mentioning that MH and GJ are among the most industrialized states in India[9]. According to the 2001 Census, MH has recorded the largest number of migrants (2.3 million), followed by DL (1.7 million)[10]. It is observed that during a pandemic, reverse migration translates to the formation of entry points of diseases. A recent study on COVID-19 indicates that restriction on human mobility can curtail the spread of disease[11].

India is a tropical country with varied weather patterns across different regions, monsoon being the most prominent

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feature. Pandemics like H1N1 are found to reach their peaks in the monsoon and winter months with spatial variation[12–16]. Water bodies have a strong influence on the microclimate of a region in terms of temperature and humidity[17–19]. This eventually contributes significantly to regional climate change and is commonly known as the lake effect[20]. In this study, we explore the temperature variations across districts with proximity to large water bodies and decode the spread of COVID-19 in these regions.

The present study aims to develop a pandemic response strategy which will help take timely preventive measures in future outbreaks. It also intends to give a thorough insight into how a disease spreads in India.

Data

This study used COVID-19 time-series data of daily infected cases for 640 Indian districts. The daily confirmed cases were obtained from the World Health Organization (WHO) website and other public sources like Worldometer and COVID-19 dashboard in India (https://www.covid19-india.org/) from 1 April to 25 December 2020. We have divided the analysis into three seasons: pre-monsoon (April 1 to June 15); monsoon (16 June to 31 August); and post-monsoon (1 September to 25 December).

Materials and method

Using the *k*-means clustering algorithm we were able to identify areas out of the total 640 districts of India which were most affected by the pandemic during monsoon and post-monsoon. In epidemiology, the basic reproduction number, commonly known as R_0, quantifies disease spread and finds the expected number of cases directly generated by one case in a population. We calculated R_0 of COVID-19 daily reported cases using exponential growth method.

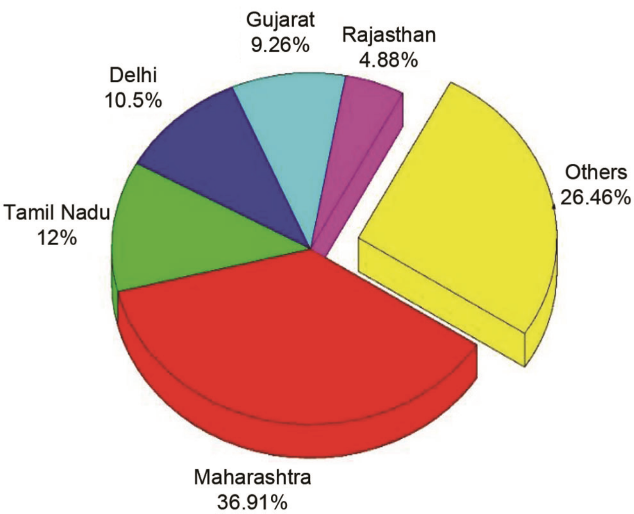

Figure 1. Distribution of COVID-19 confirmed cases in India as on 31 May 2020.

K-means is a clustering technique to amalgamate a dataset into a pre-specified number of clusters[21]. We implemented the algorithm using 'Ckmeans.1d.dp' using R software package. To narrow down the districts which witnessed a sudden increase in infected cases during the monsoon period, different k values were used. It was observed that for $k = 5$, the error was minimum. Then the *k*-means algorithm allocates each observation precisely to one of the k newly built clusters. In this algorithm, variation in data is minimized within the cluster, i.e.

$$\underset{a_{1,\dots,}a_k}{\text{minimize}} \left\{ \sum_{i=1}^{k} W(a_i) \right\}, \tag{1}$$

where $a_1, a_2, ..., a_k$ denote sets containing the indices of the observations in each cluster and $W(a_i)$ is within the cluster variation.

Algorithm: (i) We initially assign a number from 1 to k to each of the observations. These serve as initial cluster assignments for the findings. (ii) Repeat until the cluster assignments stop changing: (a) For each of the k clusters, compute the cluster centroid. The kth cluster centroid is the vector of the p feature means for the observations. (b) Assign each observation to the cluster whose centroid is the closest (where 'closest' is defined using Euclidean distance). The mathematical expression for the exponential growth model for R_0 is given by

$$R_0 = \frac{1}{\int_0^{\infty} e^{-kt} g(t) \mathrm{d}t}, \tag{2}$$

where k is the exponential growth rate. The time lag between infection in a primary case and a secondary case is defined by $g(t)$. A detailed guide to calculate R_0 using the exponential growth model is available in the literature[22,23]. We have implemented the exponential growth method using 'R_0 package' in R version 4.0.2 software. Gamma distribution with mean 4 and standard deviation 2 was used for time-interval generation. For vaccination coverage, the following formula was used

$$V_c = 1 - \frac{1}{R_0}, \tag{3}$$

where V_c denotes the vaccination coverage and R_0 is the basic reproduction number.

Results

Let us now discuss the findings of the study along with the focal points of the pandemic and the influence of climate on COVID-19 transmission rate in India.

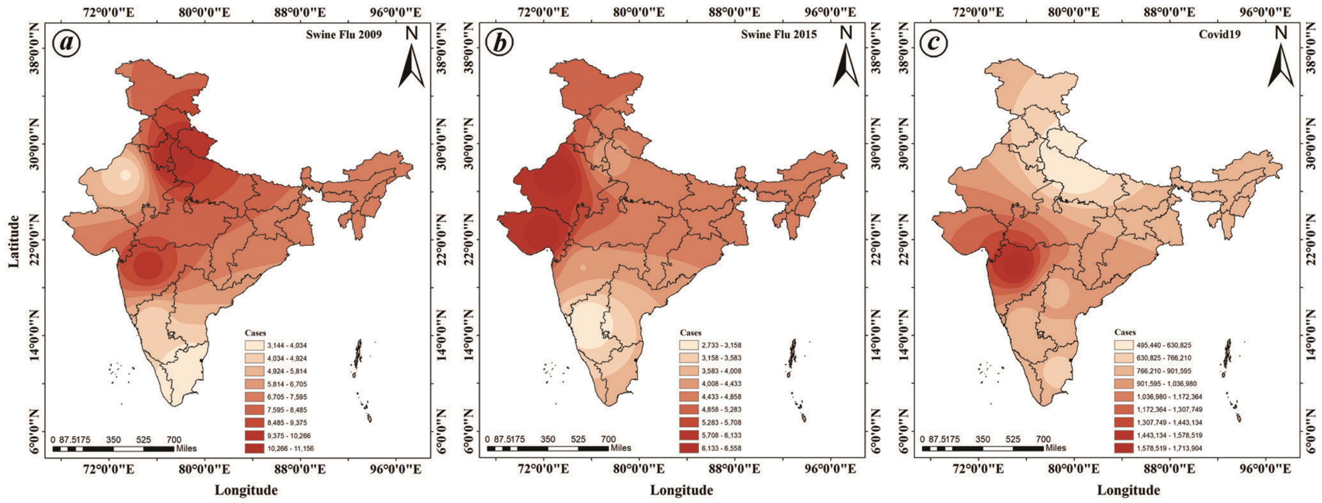

Figure 2. Hotspots of pandemics in the Indian states. ***a***, Swine flu (2009–10); ***b***, Influenza H1N1 (2014–15); ***c***, COVID-19 (2019–20).

Focal points and trajectories of various pandemics in India

There has been a striking similarity in the focal point and route of transmission of different epidemics in India, such as Spanish flu (1918–19), H1N1 (2014–15), Swine flu (2009–10) and COVID-19 (2019–21). Figure 2 shows the hotspots of these pandemics. They mostly started and found their epicentres in India's northern, western and southern parts. The situations these pandemics have created worldwide, have been the same, with similar symptoms and stigma. It is pertinent to note that most of these pandemics achieved their peak in the monsoon months. Therefore, it is vital to understand the transmission trajectory and its relationship to local climate.

Sufficient data on Spanish flu (1918–19) is not available, but in India, the pandemic broke out in the erstwhile Bombay region in June 1918, with one of the possible routes being through ships ferrying returning troops after the First World War in Europe[24]. The outbreak then spread across the country from west and south to east and north. The Spanish flu caused a staggering 12–13 million deaths and hit its peak in October.

Figure 2 *a* shows the swine flu (2009–10) hotspots. The first case of H1N1 in India was a US returnee who had landed at the Hyderabad airport in Andhra Pradesh (AP) on 16 May 2009 (ref. 25) and the rate of transmission increased in the beginning of August. On 24 May 2010, the total confirmed cases of swine flu reached 10,193 with 1035 deaths. The five most affected states were DL, AP, KA, TN and MH.

The H1N1 influenza (2014–15) spread mostly in the northern and western states of India (Figure 2 *b*) and the main hotspots were GJ, RJ, DL, MH, etc.[8,26]. The year 2015 saw the most number of swine flu cases since 2009, followed by the year 2017. The cumulative number of reported cases reached 42,592 and 38,811 respectively, in 2015 and 2017.

As shown in Figure 2 *c*, COVID-19 mainly entered India through Kerala. A recent study[27] has traced the maximum number of international contacts in Kerala in the early phase of this pandemic[27]. In the past few months, COVID-19 hotspots have changed. Figure 3 shows the number of cases in the top five affected states during pre-monsoon, monsoon and post-monsoon periods. MH, AP, TN, KA and Uttar Pradesh (UP) are among the most affected states up to 25 December 2020. MH was among the worst affected states across seasons, and cases increased from 1.1 lakh to 19.03 lakhs in the state by 25 December 2020. Also, during the monsoon season, there was an increase in cases in AP and KA.

Influence of climate on local transmission rate

Regions located in relatively lower temperature ranges have shown a rapid increase in COVID-19 cases compared to those situated in warmer climatic regions, despite their better socio-economic conditions[28,29]. Evidence suggests that 60% of the COVID-19 cases were reported in areas with 5–15°C temperature[17]. Approximately 73.8% of the patients were reported in regions with absolute humidity of 3–10 g/m^3. Also, at higher temperatures (around 40°C), the life span of the virus was found to reduce compared to lower temperatures (approximately 20°C)[17]. The lifespan of the virus was reported to be between 1.7 and 2.7 days at 20°C (ref. 17).

This temperature range increases the chances of propagation among the population[30]. Water bodies such as lakes, rivers and sea coasts significantly affect the climate of the surrounding areas[31–33]. A recent study showed that Sukhna lake in Chandigarh city and the Sabarmati river in

Table 1. Range of rainfall, relative humidity and maximum and minimum temperatures in July for all the districts of India along with 47 selected districts

		Rainfall (mm)	Relative humidity (%)	Maximum temperature (°C)	Minimum temperature (°C)
For the selected 47 districts	Highest	19.32	95.23	35.29	26.29
	Lowest	4.95	56.37	26.92	18.8
For all the districts of India	Highest	48.55	98.21	39.68	29.22
	Lowest	0.14	36.88	24.29	15.34

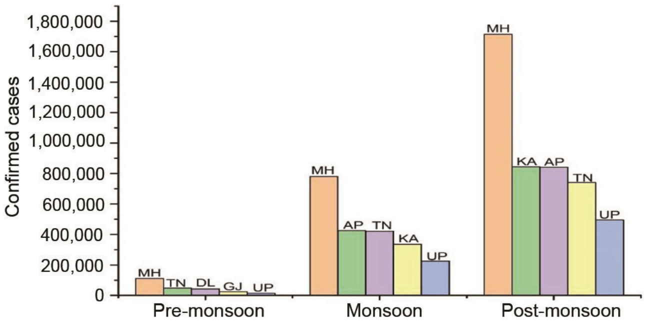

Figure 3. Changing hotspots of COVID-19 in India.

Ahmedabad played a significant role in reducing the temperature of the surrounding areas[34].

Figure 4 shows the 47 districts (using *k*-mean clustering) where a relative increase in cases during monsoon is observed, with the rise being as high as 95–800%. Concurrently, all the selected districts have direct access to large water bodies, translating to cooler temperatures. The average minimum and maximum temperature in these districts is about 3°C and 5°C respectively lower than their neighbourhoods during July (Table 1); this is attributed to the lake effect. The cooler climate conditions may have resulted in the number of cases rising in districts with proximity to water bodies. Further, we have estimated R_0 values for these districts until 31 August. The results reveal that the R_0 values are much higher than those of the primary hotspot states. For example, R_0 for Jiribam district, Manipur (MN) is 9.27, which implies that 89% of the population will have to be vaccinated, and is the highest in the selected districts. Similarly, R_0 for Narayanpur district in Chhattisgarh (CG) is 2.37, which implies that 57% of the population needs to be immunized. Table 2 shows the summary statistics of these districts; the R_0 values are also given. The transmission rate in the leading hotspot states, viz. MH, AP, TN, KA and UP was 1.11, 1.26, 1.12, 1.22 and 1.26 respectively on 31 August 2020.

During winter season, 59 districts were identified to experience a sudden relative increase compared to the monsoon season (>91.2%; Table 3). Some of these districts are close to water bodies and most are located in the Western Ghats which experiences heavy rainfall during winter, and have a mean temperate range from 20°C to 24°C. Though the transmission rate stabilized across the country in the winter season (Table 3), the northern regions witnessed the highest increase in the number of cases (Figure 4). The complete trajectory of COVID-19 is shown in Figure 4, where hotpot states during different seasons are marked, and districts with a relative increase in cases during monsoon and post-monsoon are coloured in red and blue respectively. After studying the major pandemics of the last century that have impacted India, we could identify a spread pattern. A better understanding of the pandemic progression and its relationship to seasons and geography will help us better prepare for future outbreaks.

Discussion

There is a striking similarity in the focal point and route of transmission of different pandemics such as influenza (1918–19), H1N1 (2014–15), swine flu (2009–10) and COVID-19 (2019–20). An in-depth analysis of historical data reveals that pandemics mainly entered India through the northern, western and southern states like MH, TN, Kerala, etc. Whereas DL, GJ, RJ, MH and KN have invariably constituted significant hotspots. These states have high international migration and also contribute the most to India's GDP. With this understanding, the Government should develop a more tailor-made and targeted approach in these states in case of an outbreak in the future.

Evidence suggests that most of the COVID-19 cases were reported in regions with 5–15°C temperature. Furthermore, this temperature range increases the chances of infection spreading in the population. The results revealed that individual Indian districts witnessed a sharp relative increase in the reported cases (up to 800%) during monsoon. Interestingly, most of these districts are close to large water bodies like lakes and rivers. We estimated R_0 values for these districts, which were much higher than those of the primary hotspot states. These districts

Table 2. Districts with population densities, water bodies and percentage of relative change in cumulative cases from pre-monsoon to monsoon period

District (state)	Population density (sq. km)	Water body	Relative change in cumulative cases (%)	R_0	V_c (%)
Chittoor (Andhra Pradesh; AP)	275	Neeva river	97.2	1.28	21.87
Cuddapah (AP)	188	Penna river	97.61	1.17	14.52
East Godavari (AP)	477	Godavari river	147.54	1.58	36.70
Prakasam (AP)	192	Coastal district	212.5	1.24	19.35
Srikakulam (AP)	462	Godavari river	409.73	1.20	16.66
Visakhapatnam (AP)	384	Coastal district	161.17	1.63	38.65
Vizianagaram (AP)	358	Nagavali, Suvarnamukhi, Vegavathi, Champavathi, Gosthani and Kandivalasa rivers	266.39	1.21	17.35
West Godavari (AP)	490	Godavari, Yerrakaluva and Tammileru rivers	117.09	1.32	24.24
East Kameng (Arunachal Pradesh; AR)	19	Kameng river	209	2.21	54.75
Papum-Pare (AR)	61	–	121.9	1.68	40.47
Upper Subansiri (AR)	12	Subansiri river	138	3.61	72.29
Dibrugarh (Assam; AS)	393	Brahmaputra river	104.98	1.54	35.06
Bastar (Chhattisgarh; CG)	87	Indravati river	132.16	1.23	18.69
Bijapur1 (CG)	35	Indravati river	440	1.42	29.57
Dantewara (CG)	59	Shankhini and Dankini rivers	117.33	1.20	16.66
Narayanpur (CG)	20	–	452	2.37	57.80
Sukma (CG)	49	Sabari river	513	1.43	30.06
Daman (Daman and Diu; DD)	2651	Daman Ganga river	142.14	1.13	11.50
North Goa (Goa)	471	Chapora and Mandovi rivers	353.42	1.20	16.66
Morbi (Gujarat; GJ)	197	Machhu and Fulki rivers	126.71	1.24	19.35
Devgarh (Jharkhand, JH)	602	–	111.27	1.77	43.50
Dumka (JH)	300	Mayuraskhi river	121.4	1.36	26.47
Gooda (JH)	622	–	401	2.43	58.84
Sahebganj (JH)	719	Gange river	184.75	1.22	18.03
Bangalore Rural (KA)	441	Vrishabhavathi river	119.07	1.50	33.33
Bengaluru Urban (Karnataka; KA)	4378	Vrishabhavathi river	173.29	1.14	12.28
Bellary (KA)	300	Narihalla river	103.94	1.37	27.00
Chamarajanagar (KA)	200	Kaveri river	1156.5	1.24	19.35
Chikmagalur (KA)	158	Tunga and Bhadra rivers	195.85	1.23	18.69
Gadag (KA)	229	Tunga and Bhadra rivers	101.48	1.20	16.66
Haveri (KA)	331	Kumadvati river	149.35	1.25	20.00
Kodagu (KA)	135	Kaveri river	352	1.20	16.66
Koppal (KA)	250	Hirehalla river	345.5	1.28	21.87
Mysore (KA)	437	Kabini, Kaveri and Hemavati rivers	150.57	1.22	18.03
Ramnagar (KA)	303	Arkavathi and Vrishabhavathi rivers	144.27	1.15	13.04
Tumkur (KA)	253	Jayamangali river	125.57	1.19	15.96
Thiruvananthapuram (Kerala; KL)	1509	Karamana and Killi rivers	117.75	1.24	19.35
Alirajpur (Madhya Pradesh; MP)	229	–	139.25	1.23	18.69
Jiribam (Maharashtra; MN)	190	Jiri river	114	9.27	89.21
Koraput (Odisha; OD)	156	Kolab and Jalaput reservoirs	184.72	1.28	21.87
Nabarangapur (OD)	230	Tel and Indravati rivers	354.33	1.22	18.03
Rayagarha (OD)	136	Mahanadi river	365	1.30	23.07
Sambalpur (OD)	158	Mahanadi river	107.88	1.28	21.87
Karaikal (Puducherry; PY)	1275	Arasalar river and coastal district	172.6	1.24	19.35
Yanam (PY)	1854	–	883	1.23	18.69
Pudukkottai (Tamil Nadu; TN)	348	Coastal district	99.47	1.17	14.52
Lalitpur (Uttar Pradesh; UP)	242	Shahjad, Sajnam and Jamani reservoirs and Betwa river	319	1.21	17.35

experience significant temperature and humidity change during monsoon, contributing mainly to the pandemic growth in them. For example, a substantial difference in minimum temperature (0.66–3.55°C) and specific humidity (0.0018–0.0059 g/kg) from pre-monsoon to monsoon season was calculated from the data. The average temperature in these districts is less during monsoon and winter compared to districts further from the water bodies.

Recommendations for the future

Following are the future directions to combat an outbreak more effectively.

A targeted approach

States like MH, TN, GJ, RJ, KN, DL, UP and AP have been the main hotspots of the COVID-19 pandemic in

Table 3. Districts with population densities, water bodies and percentage of relative change in cumulative cases from monsoon to post-monsoon period

District (state)	Population density (sq. km)	Water body	Relative change in cumulative cases (%)	R_0	V_c (%)
Alappuzha (KL)	1501	Western Ghats range	93.97	1.16	13.79
Angul (OD)	199	–	93.14	1.18	15.25
Anuppur (MP)	200	Son river	91.87	1.20	16.66
Balod (CG)	234	–	93.93	1.09	8.25
Balrampur (UP)	642	Rapti river	95.38	NA	NA
Bokaro (JH)	716	–	92.99	1.32	24.24
Chhindwara (MP)	177	Kulbehra river	91.21	1.16	13.79
Chitradurga (KA)	197	Western Ghats range	93.15	1.15	13.04
Dantewada (CG)	59	–	92.28	1.29	22.48
Dhamtari (CG)	394	Mahanadi river	93.07	1.39	28.05
Dindori (MP)	94	Narmada river	91.49	1.17	14.52
Durg (CG)	391		94.32	1.20	16.66
Ernakulam (KL)	1069	Western Ghats range	95.43	1.15	13.04
Gondia (MH)	253	–	95.19	1.25	20.00
Hamirpur (Himachal Pradesh; HP)	268	Beas river	95.35	NA	NA
Hisar (Haryana; HR)	815	–	91.76	1.09	8.25
Hoshangabad (MP)	185	Narmada river	91.97	1.17	14.52
Idukki (KL)	254	–	91.09	1.09	8.25
Jammu (Jammu and Kashmir; JK)	596	–	93.13	1.26	20.63
Janjgir Champa (CG)	421	–	92.19	1.19	15.96
Jhargram (West Bengal; WB)	370	Kangsabati and Subarnarekha rivers	93.3	1.17	14.52
Jharsuguda (OD)	274	–	92.99	1.22	18.03
Jind (HR)	493	–	91.08	1.18	15.25
Kabeerdham (CG)	180	–	93.86	1.26	20.63
Kalahandi (OD)	199	–	92.05	1.14	12.28
Kannur (KL)	852	Western Ghats range	93.95	1.18	15.25
Kendrapara (OD)	545	Chitropatala, Luna, Karandia, Gobari, Brahamani, Birupa, Kani, Hansua, Baitarani, Kharasrota and Paika rivers	91.6	1.19	15.96
Kishtwar (JK)	30	Chenab river	93.91	1.21	17.35
Kollam (KL)	1056	Western Ghats range	95.14	1.19	15.96
Kondagaon (CG)	74	–	91.32	1.19	15.96
Korba (CG)	183	Hasdeo river	94.94	1.10	9.09
Kottayam (KL)	896	Western Ghats range	94.9	1.07	6.54
Kullu (HP)	79	Beas river	91.36	1.14	12.28
Kurukshetra (HR)	630	–	91.64	1.23	18.69
Malappuram (KL)	1058	Western Ghats range	94.3	1.17	14.52
Mandi (HP)	253	Beas river	95.15	1.13	11.50
Mansa (Punjab; PB)	350	–	91.03	1.22	18.03
Nagpur (MH)	470	Western Ghats range	92.28	1.11	9.90
Namakkal (TN)	506	Western Ghats range	91.55	1.15	13.04
Nuapada (OD)	157	–	91.21	1.25	20.00
Palakkad (KL)	627	Western Ghats range	92.85	1.15	13.04
Pathanamthitta (KL)	453	Western Ghats range	91.36	1.06	5.66
Pauri Garhwal (Uttarkhand; UK)	129	–	92.24	1.09	8.25
Puri (OD)	488	–	91.12	1.21	17.35
Raipur (CG)	310	Mahanadi river	92.25	1.23	18.69
Rajnandgaon (CG)	191	–	93.66	1.21	17.35
S.A.S. Nagar (PB)	830	–	91.29	1.22	18.03
Sangli (MH)	329	Western Ghats range	92.26	1.25	20.00
Shahdol (MP)	172		94.07	1.15	13.04
Shimla (HP)	159	–	95.33	1.15	13.04
Sirsa (HR)	303	–	91.84	1.19	15.96
Thiruvananthapuram (KL)	1509	Western Ghats range	91	1.13	11.50
Tiruppur (TN)	–	Western Ghats range	92.45	1.20	16.66
Tumakuru (KA)	253	Western Ghats range	91.07	1.13	11.50
Upper Dibang Valley (AP)	1	Ahui, Emra, Mathun, Dri, Tangon, Ithun and Ange rivers	92.77	1.45	31.03
Wardha (MH)	205	Western Ghats range	91.79	1.25	20.00
Wayanad (KL)	383	Western Ghats range	92.25	1.08	7.40
Yamunanagar (HR)	687	–	91.55	1.29	22.48

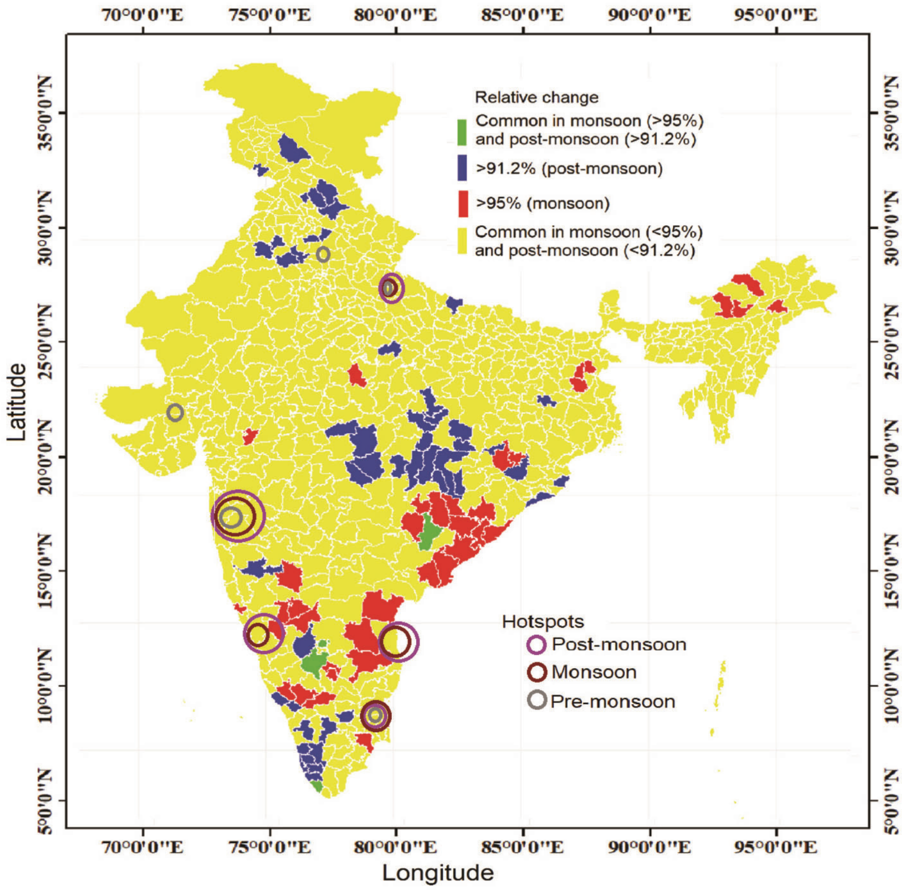

Figure 4. Trajectory of COVID-19 in India across different seasons.

India. Also, these states have been primary contributors to international migrations. Therefore, in case of a future outbreak, travel to and from these states should be monitored.

Special attention to districts with water bodies

Monsoon has been reported to be a substantial cause of disease spread in India. In the present work, 47 and 59 districts have been identified, which experienced a marked increase in the cases during monsoon and post-monsoon season respectively. This is mainly due to the presence of large water bodies in these districts. Strict precautionary measures should be imposed in these districts before the beginning of the monsoon season during an outbreak.

Micromanagement of vaccination

Due to high R_0 observed during monsoon in the study districts, if immunization is available, priority should be given to these districts.

A robust emergency plan to mitigate the spread of the next pandemic needs to be developed. Also, knowledge of regions on the trajectory of a pandemic will help better manage a future outbreak.

Conflict of interest: Authors declare no conflict of interest.

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