Assessment of temporal trend of COVID-19 outbreak in India

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Abstract

The COVID-19 pandemic has outspread obstreperously in India. Within a period of 95 days, from March 02 to June 04, India surpassed 2 lakh in count of infected cases. Approximately 3 out of each 1000 people in India has been tested till date and 53 per 1000 tests results positively infected. During the first week of March, only 14 out of each 1000 tests were resulting as positively infected and it has been extended at a rate of 71/1000 tests in the first week of June, which may indicate a sign of community spread of this disease. Mann-Kendall test denotes that the count of daily confirmed cases is significantly increasing with estimated Sen's slope of ~ 76 persons/day in entire country. This trend has escalated from ~ 5 persons/day in March to ~ 249 persons/day in the very first week of June. Among major affected cities, Mumbai and Delhi are noted with extremely high rate of increase. In the 3 out of 5 megacities in India: Delhi, Mumbai, and Chennai, the count of daily transmission have reached beyond of 1200 after the third week of May which indicate that the allowance to the migrants might make an easy-way of coronavirus transmission. Additionally, Pettitt test indicates an abrupt change in increasing trend over entire country on April 17, 2020. The nationwide transmission rate was ~ 22 persons/day before April 17 and afterward it amplified to ~ 174 persons/day. Moreover, all the major affected cities also registered multi-fold increase in transmission rate after the evaluated change point over that city; explicitly, this increment was more than 20 times over Pune, Chennai and Ahmedabad. Therefore, the nationwide imposed lockdown in India might have very less impact on flattening the curve of daily confirmed case.

Keywords:

COVID-19; weather; temporal trend; India

1. Introduction

In human history, it is apparent that pathogens have caused devastating consequences in social wellbeing and economy (Briz-Redón and Serrano-Aroca, 2020). The recent novel coronavirus disease (COVID-19) is one of the prominent example of such a disastrous event that has grasped the world. The earliest outbreak of COVID-19 caused by Severe Acute Respiratory Syndrome CoronaVirus-2 (SARS-CoV-2) happened in Wuhan, Hubei Province, China during the late December, 2019, (Guan et al., 2020; Wu and McGoogan, 2020; Zhu et al., 2020; Zu et al., 2020). Because of human-to-human transmissibility of the virus (Wang et al., 2020a; 2020b), the circumstances become progressively unpredictable and vulnerable in terms of transmission of this disease. Considering the rapid turnaround, the World Health Organization (WHO) declared an international public health emergency on January 30, 2020, and later on March 11, 2020, WHO declared this disease as global pandemic due to speedy blowout of infections. Till June 04, 2020, a total of 6,709,724 cases have been affirmed with 5.85% deaths worldwide (https://www.worldometers.info/coronavirus). Despite the fact India has registered its first case on January 29, 2020, the outbreak occurred March 2, 2020 onwards and as of June 04, 2020, a total of 226,722 cases have been confirmed; however, the death rate (2.81%) is quite lower than the worldwide situation.

Clinical investigations on COVID-19 identified respiratory droplets as the most common agent of this infection (Ge et al., 2013; Huang et al., 2020). The reported symptoms are also quite analogous to the other coronavirus diseases such as MERS and SARS, e.g. moderate to high fever with dry cough, and difficulty in breathing attributable to respiratory disorder in early stage, while it causes kidney failure, pneumonia in severe phase (Holshue et al., 2020; Perlman, 2020; Tan et al., 2005; Wang et al., 2020c).

Environmental factors, such as daily weather and long term climatic conditions may affect the epidemiological dynamics of this type of infectious disease (Dalziel et al., 2018; Yuan et al., 2006). Daily air temperature and relative humidity may impact on the transmissions of coronavirus by affecting the persistence of the viral infections within its transmission routes (Casanova et al., 2010). A few studies accounting climate and weather conditions found that these factors considerably affect the spatial distribution along with its incubation period (Bedford et al., 2015; Lemaitre et al., 2019; Sooryanarain and Elankumaran, 2015). At the earliest, Bull (1980) reported that the mortality rate of pneumonia is profoundly associated with the changes in weather condition. Studies have revealed that among different climatic variables the air temperature affects the influenza epidemics mostly in tropical regions (Tamerius et al., 2013) whereas the mid-latitudinal temperate regions experience the influenza diseases epidemics mostly during winter months (Bedford et al., 2015; Sooryanarain and Elankumaran, 2015). Nevertheless, the response to weather pattern on COVID-19 transmission found quite debatable, since, the studies carried out in different countries in the world suggested an existing correlation between weather and COVID-19 pandemic likewise that it occurs with other influenza infections (Ficetola and Rubolini, 2020; Liu et al., 2020; Ma et al., 2020; Oliveiros et al., 2020; Qi et al., 2020; Tosepu et al., 2020). Contradictorily, few studies have reported that meteorological observations are not correlated with outbreak pattern (Jamil et al., 2020; Mollalo et al., 2020; Shi et al., 2020; Xie and Zhu, 2020). Studies carried out by Wang et al., 2020a; Wang et al., 2020b suggested that the spread of disease supposed to be decreased with an increase in temperature. Gupta et al. (2020a) also predicted lowering of transmission in warmer conditions in India. However, in view of the long term climate record, Gupta et al., 2020b found, comparatively hot areas in India are possibly going to be more affected by this disease. Thus, the present study is aimed to understand the temporal pattern, and abrupt changes in COVID-19 transmission in India.

2. Data and Methodology

2.1 Data collection

India, the largest country in South Asia, extended from 6° N to 38° N and 68° E to 98° E, comprising a land area of 3.287 million sq. km. with a total population of more than 1.2 billion (Census, 2011). The data of daily COVID-19 cases were collected from the official website of the Ministry of Health of India (https://www.mohfw.gov.in). Among 725 districts in India, more than 85% has reported multiple confirmed cases. Several studies have reported that the disease spread at a higher rate in the cities where population is very high (Ahmadi et al., 2020; Bonasera and Zhang, 2020; Casanova et al., 2010; Kang et al., 2020; Rocklöv and Sjödin, 2020). Thus, among 53 'million cities' (where the total population is more than one million) in India, 9 cities have been selected for this study, from where more than 79% of total cases in India have been reported till June 4, 2020 (Fig. 1).

2.2 Mann-Kendall Test

The nonparametric Mann-Kendall (MK) method (Kendall, 1975; Mann, 1945) was applied to the daily data of COVID-19 confirmed cases during March 01 to June 04, 2020 to detect statistically significant trends. The MK test account the null hypothesis (H_0) as there is no trend in the count of confirmed cases of infections; while the alternate hypothesis (H_1) indicate a trend (increasing or decreasing) over time. The mathematical expressions for calculating MK Statistics S, $V(S)$ and standardized test statistics Z are as follows

$$S = \sum_{i=1}^{t} \sum_{j=t+1}^{T} sgn\left(X_j - X_i\right), \tag{1}$$

$$sgn\left(X_j - X_i\right) = \begin{cases} +1 & if\ \left(X_j - X_i\right) > 0 \\ 0 & if\ \left(X_j - X_i\right) = 0 \\ -1 & if\ \left(X_j - X_i\right) < 0 \end{cases} \tag{2}$$

$$V(S) = \frac{1}{18}\left[T(T-1)(2T+5) - \sum_{p=1}^{q} t_p\left(t_p - 1\right)\left(2t_p + 5\right)\right] \tag{3}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR\ (S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{\sqrt{VAR\ (S)}} & if\ S < 0 \end{cases} \qquad (4)$$

where, X_i and X_j are the daily observations, T is the length of time series, t_p is the number of ties for p^{th} value. Positive Z values designate an increasing trend and negative Z values signpost a negative trend. For $|Z| > Z_{1-\alpha/2}$, H_1 is accepted with rejection of H_0 considering the critical value of $Z_{1-\alpha/2}$ for a p value of 0.05 as 1.96.

2.3 Sen's Slope Estimator

Sen's slope (Sen, 1968) is widely employed to estimate the magnitude of trends.

$$T_i = Median \left[\frac{x_j - x_k}{j-k}\right] for\ all\ j > k \qquad (5)$$

where, x_j and x_k represent the corresponding data values at time j and k.

$$Q_i = \begin{cases} T_{(N+1)/2} & if\ N\ is\ odd \\ \frac{1}{2}\left(T_{N/2} + T_{(N+2)/2}\right) & if N\ is\ even \end{cases} \qquad (6)$$

A positive Q_i value denotes an increasing trend; a negative Q_i value signifies a decreasing trend.

In this study, MK test and Sen's Slope Estimator were implemented to investigate the trend of daily transmission over selected cities as well as all over the country. It helped to get to know whether the temporal pattern of transmission varies in different cities with respect to countrywide pattern or not.

2.4 Pettitt test

Originally developed by Pettitt (1979), the non-parametric Pettitt test is an effective method of perceiving the change in temporal trend in any time series analysis because of its sensitivity to breaks in the middle of temporal records (Gao et al., 2011; Hänsel et al., 2016; Jaiswal et al., 2015; Mallakpour and Villarini, 2016; Wijngaard et al., 2003). In this method, S is evaluated for all random variables from 1 to T; then the most prominent change point is determined where the value of $|S|$ found to be largest:

$$K_T = max_{1 \leq t < T}|\mathrm{S}| \quad (7)$$

At particular time t, the change point is detected when K_T is ominously different from zero at any particular level where the significant level is estimated by:

$$p = 2 * \exp\left(\frac{-6K_T}{T^2 + T^3}\right) \quad (8)$$

The change point can be evaluated as statistically significant only when the estimated p-value becomes lesser than the pre-assigned significance level i.e. α.

3. Results and discussion

Table 1 presents the results of MK test, Sen's slope and change point through Pettitt test. All the results are found significant at α=0.05 level, thus, there is significant change in transmission pattern. The calculated Sen's slope shows a rate of increase in COVID-19 transmission of ~76 persons/day all over the country, whereas among the selected cities, Delhi register the highest rate of increase (~11 persons/day) and Jaipur record the slowest rate of increase (1 person/day). Analyses also depict, the trend of daily new cases changed (increased) in all-over India on April 17, 2020, i.e. at the beginning of the 2nd phase of lockdown (April 15 to May 03, 2020). During the middle of April, a majority among the cities, namely, Ahmedabad, Chennai, Delhi, Indore, Kolkata, Pune and Mumbai registered the abrupt increase in between of April 12 and April 22, 2020. Only Hyderabad and Jaipur noted abrupt increase during the 1st lockdown period (March 25 to April 14, 2020). It has been also noted that all the major affected cities register 3-34 times increase in transmission rate after the evaluated change point; explicitly, this increment was more than 20 times over Pune, Chennai and Ahmedabad after the estimated change point. The nationwide transmission rate was ~ 22 persons/day before April 17 and afterward it amplified to ~ 174 persons/day. Thus all over the country specifically the most affected cities experience an alarming rate of increase in transmission during the lockdown period. Basically, the lockdown was implemented with a brief guideline of social distancing to reduce the occurrence of human-to-human transmission by avoiding the gatherings at workplaces and at any other public places. Thus, the nationwide lockdown was very effective to reduce the growth rate of transmission in different countries across the world such as China, Italy, France, Germany, United Kingdom etc. (Gatto et al., 2020; Leung et al., 2020; Wurtzer et al., 2020). However, in India, the initial growth rate up to March was approximately 5 persons/day, and after that, the growth increased multi-fold. The growth rate was ~ 49 persons/day during April; it reached up to ~ 113 persons/day during May 1 to May 20, and during May 21 to June 04, it was ~ 249 persons/day (Fig. 2). The reason behind the initial slow growth rate was lack of testing facilities as lesser than 10,000 tests/day were done during the month of March. In Fig. 3, it is observed, an average of 53/1000 tests results confirmed for infection during the entire study period, however, it was 35/1000 in the month of March; later, it reached to 44/1000 and 57/1000 during April 01-30 and May 01 - June 04, 2020 respectively. It depicts that the probability of getting confirmed cases are also increasing in each week which may be the evinced of community transmission. The trend of daily new cases in the major affected cities (Fig. 3) also indicate the high increase in daily transmission, May onwards. It also exhibits that cities located at a lower elevation and having higher population have registered a higher growth rate of transmission, thus agreed to early observation by Gupta et al., 2020c. Over the 3 out of 5 megacities in India: Delhi, Mumbai, and Chennai, the count of daily transmission have reached beyond of 1200. One of the probable reason behind such spike in transmission might be the allowance to the migrants to return their native places, instigated a large crowd in various cities and gathering in transport sectors as reported in many local and national newspapers, thus might result such an unforeseen rate of increase in daily new cases all-over the country.

4. Conclusion

In this study, the daily trend of confirmed cases in 9 most affected cities in India along with a comparison of entire country have also been inspected in this study. The COVID-19 pandemic has resulted in a state of recrudescence in India. The daily confirmed cases are uprising with a daily grade of ~ 76 persons since March 2, 2020, however, this rate of increment was noticed as approximately 249 persons/day during the last fortnight. Initially, 14 out of each 1000 tests were resulting as positively infected during the first week of March, which has been escalated at 71/1000 tests in the first week of June. On other hand, lowering of strictness in subsequent phases of lockdowns along with the consent of interstate migration had inevitably caused an easy-way for transmission, hence resulted an intractable circumstance all over the country. The cities with higher population are cataloguing a higher rate of increase in daily cases. Moreover, the progressive change in uprising trend over all the major affected cities has also been noted during mid of April, i.e., at the margin of first and second lockdown. It signifies that imposed lockdown was unsubstantiated to reduce the COVID-19 transmission in India unlike South Korea, Japan, Iran etc. Regardless of several inferences, this study had limitations since many other major affected cities were not able to incorporate due to lack of data availability. Besides, the count of immigrants from abroad or other cities and have been quarantined were not available; these might can enhance the exactitude of the current analysis.

CRediT authorship contribution statement

Amitesh Gupta: Conceptualization, Methodology, Investigation, Visualization, Writing – original draft. **Biswajeet Pradhan**: Writing – review and editing, Supervision.

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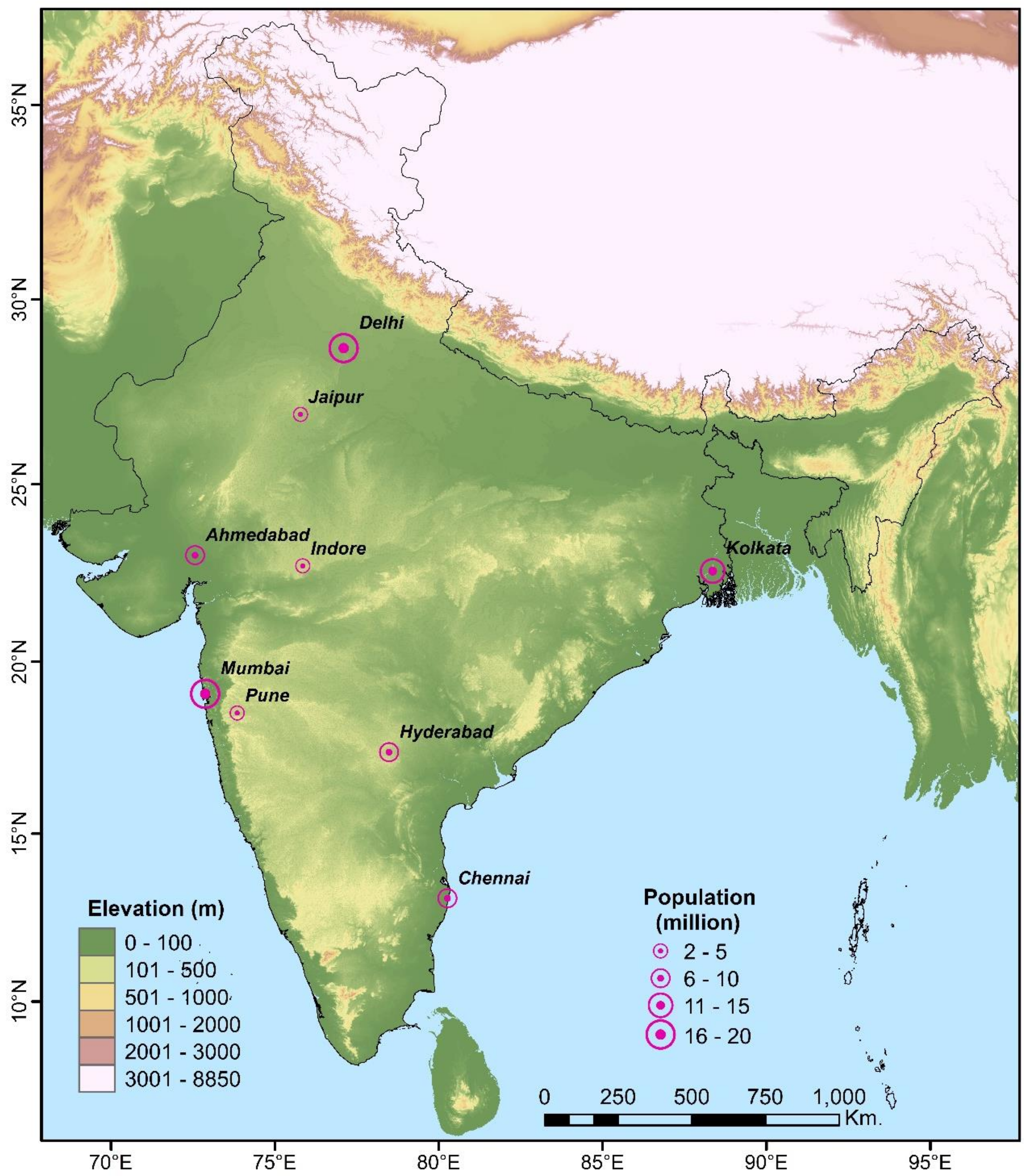

Fig. 1 Location of the selected cities in India along with the total population of those cities.

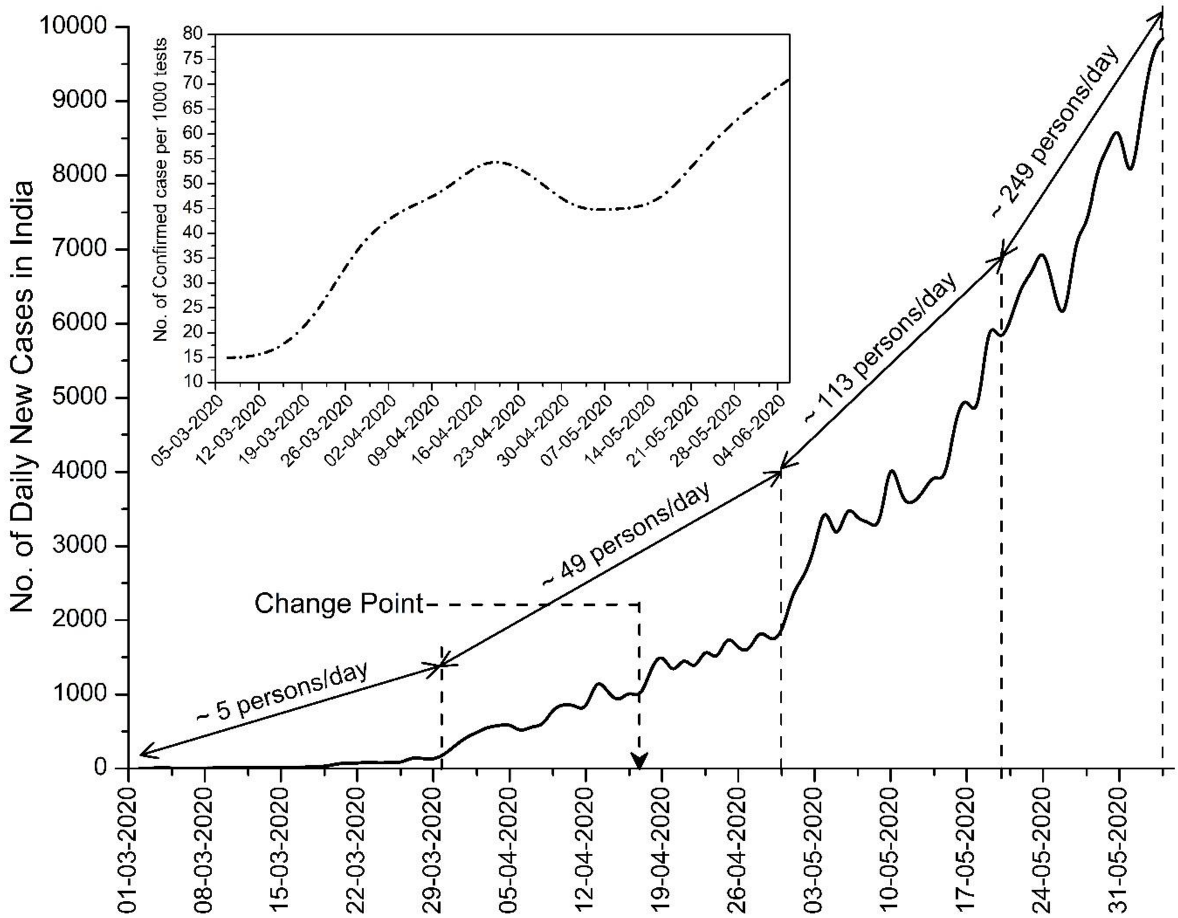

Fig. 2 Trend of daily confirmed cases in India. The weekly trend of number of confirmed cases per 1000 tests are shown.

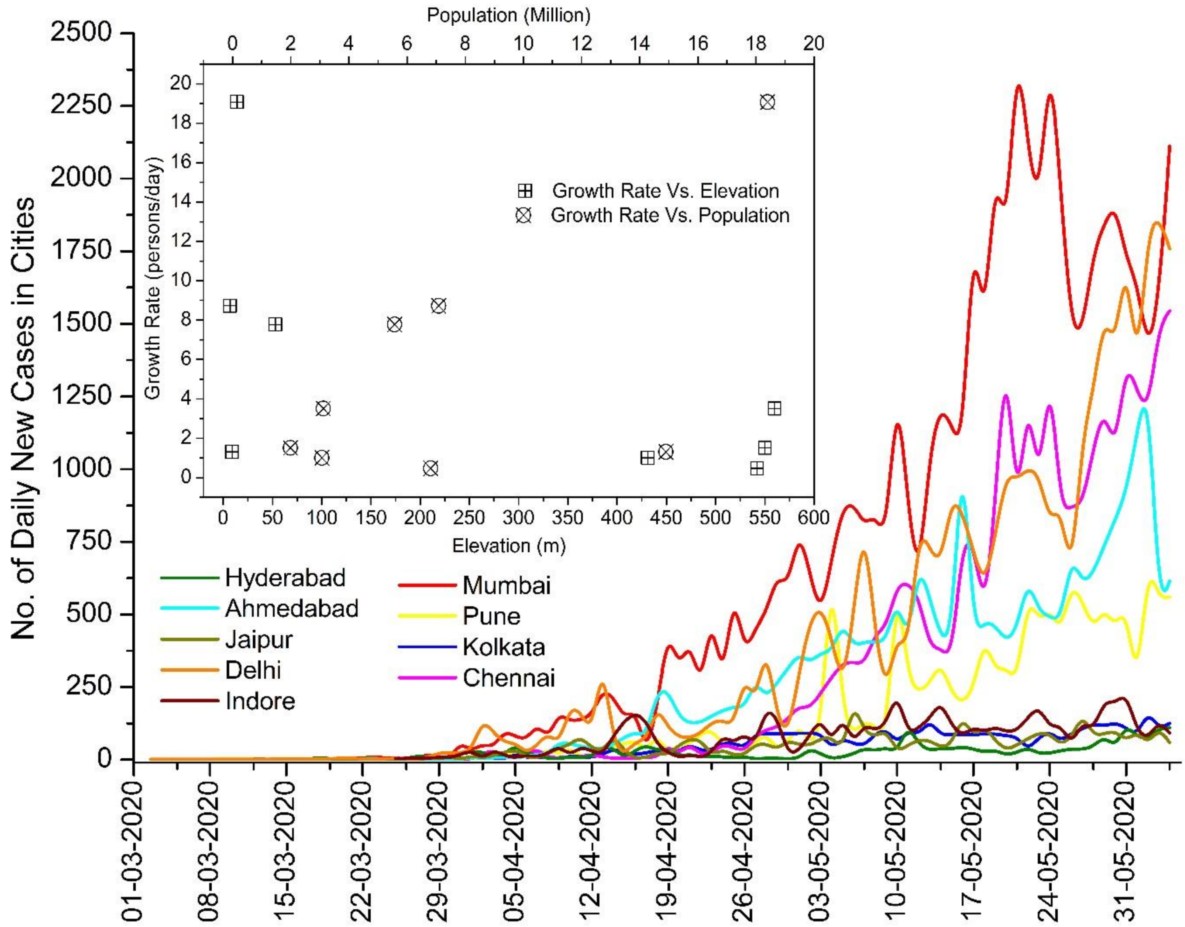

Fig. 3 The daily trend of confirmed case in selected cities are shown. In insight, the scatter graph of growth rate of transmission with respect to the population and elevation of those cities is depicted.

Table 1 Result of Mann-Kendall test, Sen's Slope, Pettit test.

	Tau	Sen's Slope	Change Point	Slope before Change Point	Slope after Change Point
Ahmedabad	0.90*	7.77*	17-04-2020	0.46*	12.75*
Chennai	0.89*	8.73*	18-04-2020	0.91*	31.28*
Delhi	0.87*	10.85*	22-04-2020	1.78*	34.86*
Hyderabad	0.63*	0.47*	31-03-2020	0.15*	0.57*
Indore	0.70*	1.5*	14-04-2020	0.43*	1.49*
Jaipur	0.70*	1*	09-04-2020	0.19*	1.08*
Kolkata	0.82*	1.3*	17-04-2020	0.25*	1.43*
Mumbai	0.88*	19.08*	18-04-2020	2.79*	38.2*
Pune	0.83*	3.51*	12-04-2020	0.52*	10.63*
All over India	0.95*	76.11*	17-04-2020	21.55*	173.54*

*Significant at 0.05 significance level.