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# COVID-19 EPIDEMIC ASSESSMENT USING THE SEEDING TIME AND DOUBLING TIME MODEL ACROSS STATES IN INDIA.

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## ABSTRACT

**Introduction**–India has witnessed a rapid increase in the number of cases and hence there is a need to characterise this growth and assess the pandemic situation in the different states of the country and over time. We aimed to develop a model to compare the situation as of now versus as it was in the beginning of the pandemic by using a seeding time, doubling time model (STDT model).

**Methodology**–Using the daily case reporting data from the Ministry of Health and Family welfare website (MoHFW) website, India. A seeding time, doubling time model (STDT model) was created to map the epidemic situation in different states across India by adopting the methodology by Zhou et al.

**Results** -The median seeding number was 294 cases (range: 9–3651). The overall mean of the 35 state/UT's individual seeding time values was 56 days (range: 22–122). The mean of the doubling time for states was 10.11 days (range: 4.33–18.66) during the initial phasewhich increased to 19.63 days. The STDT model for the two time periods depicted the movement of most of the states from high risk group to low risk groups.

**Discussion**– The states and union territories moved from high risk categories to low risk categories from the beginning of the pandemic to the present time, suggesting success of the various non-pharmaceutical interventions like social distancing, staggered work pattern, wearing of mask, cough etiquette and the myriad of sanitisation practices.

**KEYWORDS :** Seeding time, Doubling time risk assessment, COVID-19

## INTRODUCTION

The World Health Organization (WHO) declared the COVID-19 epidemic a "public health emergency of international concern" on 30 January 2020 (1), and then elevated COVID-19 to pandemic status on 11 March 2020 (2). Over the period of many months it has spread from its epicentre Wuhan, Hubei Province, PRC to nearly every country on the planet (3). By 30th July 2020, more than 16.5 million cases and nearly 650 000 deaths had been reported to WHO across the world with India reporting a cumulative of over 1.5 million cases and an excess of 35000 deaths (4). COVID19 pandemic has become the worst pandemic after the Spanish Flu of 1918 (5).

In the absence of a vaccine or a curative drug, non-pharmaceutical preventive interventions (social distancing, hand washing, cough etiquette, avoidance of mass gathering etc.) remains the mainstay of dealing with the pandemic (6). These measures while effective have an opportunity cost in the form of an economic downturn. Policy makers have to balance the public health benefits and the economic cost of lockdowns and other social distancing measures. In other words, a balance between macroeconomic considerations and the pandemic situation along with others are taken into account to make decisions regarding the implementation of various norms of social distancing including lockdowns. (7–13)

Such decisions need to be evidence based, informed by data about the potential progression of the pandemic and its effects. Many state authorities, universities, national governments and researchers have been up to the task and we have witnessed the creation of data dashboards (14–19) and the development of modelling techniques to characterise the current growth and make predictions into the future. (17,20,29–38,21,39–42,22–28)

These models are assumption-based and hence prone to errors, for example it is often difficult to account for the dynamic nature of $R_0$ which varies with geographic location and time and also in response to and fidelity of the implementation of the non-pharmaceutical interventions. (43)

The Indian government was swift to respond to the pandemic declaration by WHO and on 24 March 2020, declared a nationwide lockdown for 21 days. The lockdown was placed when the number of confirmed positive coronavirus cases in India was 562 with only 9 deaths. On 14 April, the nationwide lockdown was extended until 3rd May. On 1st May, the lockdown was extended further by two weeks until 17 May. The Government categorised all the districts into three zones based on the spread of the virus—green, red and orange—with relaxations applied accordingly. On 17 May, the lockdown was further extended till 31 May by the National Disaster Management Authority (44). Observers stated that the lockdown had slowed the growth rate of the pandemic. (38,45–47)

Lockdown restrictions were lifted from 1st June, termed Unlock 1.0 and further from 1st July, termed Unlock 2.0 (48), with this ease of restrictions and increased mobility of people, India have witnessed a rapid increase in the number of cases and hence there is a need to characterise this growth and assess whether the pandemic situation in the different states of the country.

Therefore, to minimize the impact of information gaps while still meeting the need for timely, convenient, and accurate, yet easy to understand, risk assessments for COVID-19 pandemic at the state level, we aimed to develop a simple model using case reporting data for India to assess the pandemic situation in the various statesas of now versus as it was in the beginning of the pandemic by using a seeding time, doubling time model (STDT model).

## MATERIAL AND METHODS

### Data source and analysis
Daily case reporting data (dates and cumulative number of cases) was extracted from the Ministry of Health and Family welfare website (MoHFW) website (https:// www. mohfw. gov.in/) for the whole period of analysis (from the beginning of the pandemic until 03/08/2020), the data was transferred on to an Excel sheet for further analysis (Microsoft 365 version, Microsoft Corp., Redmond, Washington, USA)

The methodology is adopted from a study conducted by Zhou et al., we used data from all the states of India to construct the seeding time, doubling time model (STDT model). All the states were used to calculate the mean seeding time (ST) and the mean doubling time (DT) which were then used to assign the coordinates for the STDT model.

### Components of the model
Two epidemiologic parameters – Seeding time (ST) and doubling time (DT) were calculated for each state at the beginning of the pandemic and for the month of July 2020. ST is the time interval, measured in days, between the date of the first case report in a state (i.e., the index case) and the date on which the cumulative number of confirmed cases reached the seeding number (SN). SN is the total number of cases required to "hatch" an epidemic in the state. It can determine the original introduced risk at the beginning of an outbreak and it influences DT. DT is the time interval, measured in days, required to double the total cumulative number of cases, and it can be an indicator of the effectiveness of control measures for and preceding the period for which it is calculated.

### Determining the seeding number
Seeding number was determined first, since the ST and DT both depended on it. It was done using the epidemiologic curves (plotted as time in days on the x-axis versus cumulative total number of cases on the y-axis) for all the states. They were assessed by the two authors who independently selected the date on which each epidemic curve appeared to "take-off". The cumulative number of cases reported up to the day before this "take-off" date was the seeding number (SN) for each state and with it the median SN for all the states was determined (Figure 1).

### Setting mean seeding and doubling times
The mean ST and mean DT were used to draw the coordinate plane for the ST/DT Model and divide it into the four quadrants. Each state's ST was calculated as the time in days it took to reach the median SN (calculated previously). The overall mean ST was then calculated by using the ST of all states. Early epidemic stage DT for each state was calculated as the mean number of days required to double the number of cases from the SN to 2×SN, then to 4×SN, and then to 8×SN cases. The mean DT for each of these state's first three doubling periods was then used to determine an overall mean DT.

### The Model structure
The ST/DT Model is illustrated in (Fig.) ST increases along the x-axis while DT increases along the y-axis. Plotting lines that represent mean ST and mean DT creates four quadrants upon which states' epidemics can be plotted. The four quadrants indicate different levels of risk— short ST and DT indicate high risk (red) compared to the low risk indicated by long ST and long DT (green). In between these high and low risk states, are long ST and short DT, ascribed moderately high risk, and short ST and long DT, ascribed moderately low risk. Since DT is more important than ST to the future of epidemics already seeded, the long ST, short DT condition is given a higher risk label than short ST and long DT.

### Validation of the model
The risk assessment of the states would change with time and with evolving conditions such as imposition of lockdown or other stricter social distancing measure or vice versa. While ST would remain unchanged, shortening or lengthening of DT should reflect changed conditions, thereby allowing states, ideally, to move from high risk to moderately low risk or from moderately high risk to low risk.

To verify that the ST/DT Model can indeed detect changes and alter resulting risk assessment, later epidemic stage mean DT was calculated using DT of all the states for the month of July 2020 using the exponential function inMS Excel. Later epidemic stage positioning of each country on the ST/DT Model coordinate plane was compared to earlier stage positioning.

The movement of the states in the various categories of risk assessment using the STDT model was compared to what was known about the epidemic and the response patterns in the states, in an attempt to validate the model.

## RESULTS
### Seeding number
All the 35states and union territorieswere included in the determination of median SN. The overall median SN was 294cases (range: 9–3651). Hence, the SN used for the ST/ DT Model was set to 294 cases.

### Mean seeding time and mean doubling time
Each individual state or union territory's ST was first calculated, using SN set to 294 cases, as the time in days it took for them to accumulate 294 cases beginning from the date of the first case. Each State or UT's DT was then calculated as the mean of its first three DTs (i.e., time from SN cases to 2xSN, from 2xSN to 4xSN, and from 4xSN to 8xSN). Each state or UT's ST and DT were then plotted on the ST/DT Model's coordinate plane (Figure1). The overall mean of the 35 state/UT's individual ST values was calculated to be 56 days (range: 22–122). So, for the ST/DT Model, mean ST was set to 56 days as shown by the vertical line on the ST/DT Model. The overall mean of the individual mean DT values was calculated to be 10 days (range: 4.33–18.66). So, for the ST/DT Model, mean DT was set to 10 days as shown by the horizontal line on the ST/DT Model (Figure 1).

### Changing risk assessment with time
The mean DT of all the states as calculated by the exponential function of the MS Excel for the month of July was 19.63 days which is statistically significantly different than the mean DT of 10.11 days at the beginning of the pandemic ('p' value <0.05). Another ST/DT coordinate plane was made with this new DT (ST remained the same) (Figure 2). Hence, many states moved from Higher risk categories to lower risk categories which was in line with the application of social distancing and other non-pharmaceutical control measures. (Table 1)

Table 1 also shows that initially at the beginning of the pandemic there were 8 states in the High-risk category as per the STDT model; 10 in the moderately high-risk category; 10 in the moderately low risk category; and, 7 in the low risk category. In the month of July, the numbers in the various categories were 0, 1, 21 and 13 respectively. This shows that number of states and union territories in the higher risk categories (high risk and moderately high risk) have decreased and their number in the lower risk categories (Low risk and Moderately low risk) have increased.

## DISCUSSION
At the beginning of the pandemic the mean seeding time for the pandemic was 55.85 days meaning that it took around 2 months on an average for a state to have a full-blown epidemic situation. This made the vertical coordinate for the STDT model.

In this phase the mean doubling time for the cases in each state (taken as the mean of the first three doubling times) was a mere 10.11 days. It meant that the cases doubled every 10 days. This made the horizontal coordinate of the STDT model.

There were 8 states which had a low seeding time and low doubling time than the mean, implying that they were at high risk of rapid rise of case. On the contrary states or Union territories that had a higher than mean seeding time and doubling time were at low risk for the spread of epidemic, there were 7 such states. Other states were either moderately high risk, n=10 (low DT and high ST) or moderately low risk, n=10 (high DT and low ST).

While the vertical coordinate for the STDT model remained the same (seeding number was unchanged) the horizontal coordinate was raised due to an increase in the mean doubling time. Because of this the risk categories shifted which was a reflection of the relative success of the various non-pharmaceutical interventions like social distancing, staggered work pattern, wearing of mask, cough etiquette and the myriad of sanitisation practices.

In the month of July the number of states in high risk category was 0 and moderately high risk, moderately low risk and low risk categories had 1, 21 and 13 states or union territories.

## CONCLUSION

The social distancing measures in India have been relatively successful as most states have shown a decline in doubling time as compared to the beginning. The same has been confirmed by a movement of the states to low or moderately low risk category of the STDT model.

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Tables and Figures

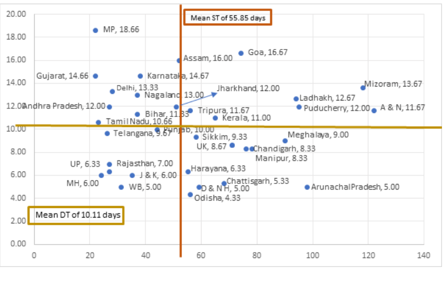


**Figure 1 – ST/DT model in the beginning of the pandemic in India**

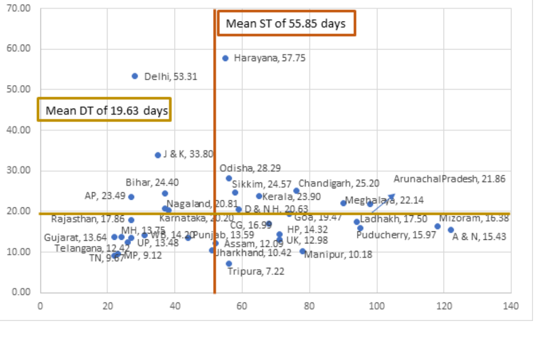


**Figure 2 – ST/DT model July 2020**

**Table 1 – Changing risk assessment of the states and UTs of India as per the STDT model from the beginning of the pandemic to the month of July 2020**

| Before | After |
|---|---|
| High Risk (8) | High Risk (0) |
| Haryana | Low Risk (13) |
| Jammu and Kashmir | Punjab |
| West Bengal | Karnataka |
| Maharashtra | Nagaland |
| Uttar Pradesh | Bihar |
| Rajasthan | Telangana |
| Telangana | West Bengal |
| Punjab | Rajasthan |
| Low Risk (7) | Andhra Pradesh |
| Tripura | Uttar Pradesh |
| Kerala | Maharashtra |
| Goa | Gujarat |
| Ladakh | Tamil Nadu |
| Puducherry | Madhya Pradesh |
| Mizoram | Moderately High Risk (1) |
| Andaman and Nicobar Islands | Tripura |
| Moderately High Risk (10) | Moderately Low Risk (21) |
| Odisha | Manipur |
| Dadar and Nagar Haveli | Chandigarh |
| Chhattisgarh | Mizoram |
| Uttarakhand | D & N H |
| Manipur | Sikkim |
| Meghalaya | Arunachal Pradesh |
| Arunachal Pradesh | Puducherry |
| Sikkim | A & N |
| Himachal Pradesh | Meghalaya |
| Chandigarh | Ladakh |
| Moderately Low Risk (10) | Goa |
| Madhya Pradesh | Himachal Pradesh |
| Gujarat | UK |
| Delhi | Chhattisgarh |
| Andhra Pradesh | Jharkhand |
| Tamil Nadu | Odisha |
| Bihar | Assam |
| Nagaland | Haryana |
| Karnataka | J & K |
| Assam | Kerala |
| Jharkhand | Delhi |

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