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Spatial Epidemiology models on Covid-19 cases in India Mathematical models and data used in Spatial Epidemiology

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Abstract

Geographical epidemiology has been description of geographical patterns of mortality rates as part of descriptive epidemiological investigations, with the goal of developing theories regarding disease causation. Disease mapping, disease clustering, and ecological analysis are the predominant methods of geographical epidemiology, having close relationships between them. For describing the transmission of an illness within a geographically dispersed population, many models incorporating frameworks based on individuals, networks, stochastic processes, as well as partial derivative equations have been made. However, these models need a large amount of information and even a large amount of computational performance. Keeping this in mind, we have tried to create deterministic models formulated as partial differential equations to model spatial epidemics in spatial domains. This has been by assuming two types of population, the susceptible population, and the infective population, considering the functions of space and time. COVID-19 is a global tragedy, with India likely to be among the most hit. The fluctuation in the dispersion of COVID-19-related well-being results is most likely connected with numerous basic factors, like segment, financial, or natural poisons related factors.

Keywords: Spatial Epidemiology, Mathematical models, COVID-19, Lockdown.

Introduction:

The COVID-19-caused pandemic of this century has turned into a significant problem for the world. According to World Health Organization records, the infection was initially discovered in the Chinese city of Wuhan. Subsequently, the virus spread to other nations by human bodily transfer, and accidentally and consciously, foreign travelers served as the virus' unwitting carriers [1]. South Asian nation, India has also been severely impacted by this. The quantity of corona pathogen positive cases in India was initially quite low, but the government there promptly took many important efforts to restrict the virus's spread throughout the nation [2]. The quantity cases in India continues progressively rising despite several measures including the restriction of visas, the closure of all higher education institutions, the need that travelers to other countries spend 14 days in confinement, the collection of samples for COVID testing, etc. India has been currently seeing a record variety of additional cases every day, or most crucially, reports of positive cases have been emerging from practically every state. Nearly 0.22 million cases has been recorded in India, just since June 5th, 2020. Despite the fact that there are now not a lot of instances compared to the total population of the nation, their severity and rate of escalation make them important. Consequently, it is possible that in the next days, the percentage of positive instances will rise. Additionally, the Indian government is expected to lift the lockdown gradually beginning on June 1st, 2020 because to the significant harm it has caused to the nation. Additionally, it will cause a sharp rise in the number of selected features.

Numerous factors have been linked to COVID-19 in recent studies, including temperature [3], pollutants [4], moisture levels [5], inhaling [6], but instead WaSH impact [7], as well as lack of resilience [8], that might also control rigorousness as well as frequency of COVID-19. Each stage of this pandemic involves the recognition of risk variables connected to epidemiological, socioeconomic, and built environments in order to effectively prevent the rise of the COVID-19 infection. Poor socioeconomic, structural, and health structures are already known to be potential contributors in the development of infectious diseases as HIV, influenza, bronchitis, pneumonia, and others [9]. These investigations could imply that this newly discovered virus has a similar trend. To gain a full picture, further research is required in the context of developing nations in various scenarios that take into account a wide range of variables. A perfect case study for analyzing the underlying factors that contribute of COVID-19 is Asia, a developing town with a resident of 1.38 billion people that aspects significant problems in a variety of areas such as underdeveloped infrastructure, joblessness, wealth injustice, poor health frameworks, etc. Additionally, most researches do not focus on these crucial elements, which must be investigated to raise awareness of this epidemic. Determining the possible influence of demographic, economical or physiological configuration on COVID-19 prevalence has been the key question that arises in this situation.

Geographic spread during epidemics is less well known and researched than illness as epidemic development and management throughout time. Realistic models for such geo-temporal evolution of epidemics, whether infectious illness, drug misuse fads, rumours, or disinformation, are clearly important. The main issue is determining whether to do and to put a figure on spatial impacts. In the study, a diffusion model for both the geographic spread of such a generic epidemic has been built and its application to a well-known historic pandemic, an endlessly captivating "mediaeval Black Death" in 1347-1350. Further, we look at workable solutions to the current rabies outbreak, that had spread through central Europe that is now threatening France's north coast. Such types of models have not been restricted to a single disease.

These environments have been transformed by global information system (GIS), which, to put it simply, allow users to examine spatial or geographic relevant data, whether it be through digital maps and perhaps other info graphics. Through use of geospatial as well as statistical tools is crucial for these goals now that Covid has now become an outbreak on a worldwide scale. Problems with disease clusters but also hotspots have already been addressed through mathematical analysis and spatial epidemiology in limited regions. These methods are employed in arising infectious disease analysis.

The collection and processing of extensive geo - referenced datasets with many variables on various geographical scales become significantly more efficient because to advancements in geostatistical approaches, giving epidemiologists new tools to include space and place in their research [10] The practitioners define regions of excess and their potential causes using the illness prevalence layouts as a tool for monitoring and preventative initiatives. Understanding and evaluating the choropleth maps involves three main challenges: (1) Extremely hazardous rates that typically come about for sparsely developed places and commonly detected COVID. (2) Graphical discrimination in arrears to including health - related data inside the provinces of enormous varying proportions and categories. (3) Spatial assistance discrepancy for something like transmission of infection and independent variables data.

In order to increase regional patterns on a broader scale while filtering out localised minor differences, geostatistical techniques have been created [11],[12]. These approaches have very different computing requirements as well as underlying principles regarding spatial patterns as well as risk value distribution. Clustering analysis is a crucial exploratory method in scientific investigation [13]. The location and event features observed, together with the accurate and appropriate handling of space and spatial linkages, are all factors that affect spatial cluster identification. To date, it has required the employment of certain structural and accounting methodologies for the distance, the surroundings, the proximity, the irregularity of the geography, and so on.

Beyond overall consequences for human health, epidemics, catastrophes, including public health emergencies are increasingly recognised as a danger to population health and people's welfare. We employ a deterministic computational model with following epidemiological hypotheses to describe the transmission of an illness within a geographically distributed population (Table 1 and Figure 1). The pandemic splits the population between three distinct groups: those who are vulnerable, those who are infective, some of whom have been infected who are not yet infective. Both birth or immigration of those other susceptible persons, as well as the rehabilitation of infective individuals, do not raise the frequency of vulnerable individuals. The virus spreads because a pathogenic individual might have an infectious impact on a vulnerable individual living in a distant location. The degree of exerted impact is determined by location between the infectious as well as susceptible individuals. The infection reduces the vulnerable population throughout proportion towards the infectious impact of the infectious agent. The proportionality factor is determined by the number of susceptible individuals. An infected person does not become infectious immediately after infection, but rather during a latent period whereby the infectious impact must be established.

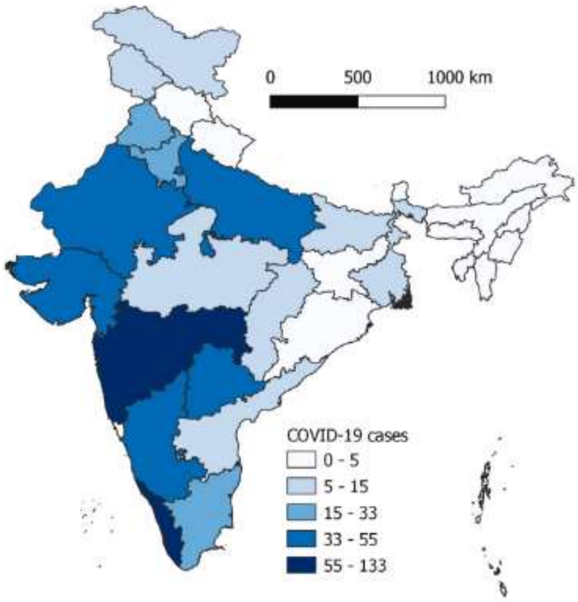

Figure 1: Covid-19 cases state-wise, India (Jan-March 2020 (Source: Kumar, A. (2020)).

Infectious outbreaks develop in geographical areas with significant spatial heterogeneity. This regional diversity is critical for evaluating the influence of health promotion programs and interventions upon epidemic control. Accounting of people's migration in spatial contexts is a fundamental challenge in constructing models to represent spatial heterogeneity in epidemics. Many techniques have been implemented to generate realistic descriptions of outbreaks in geographical contexts, comprising “individual-based models”, “network models”, “stochastic models”, “partial differential equations models” (PDE). “Individual-based”, “network-based”, “stochastic models” use social data on social mobility in addition to collaboration to mimic social behaviour at geographical plus temporal scales using probabilistic assumptions. Such models can need extensive information collection as well as extensive computational output. Our purpose is to offer an alternate method for modelling spatial epidemics that is focused on deterministic models expressed using partial differential equations in the spatial fields.

Table 1: Covid-19 statistics in India

Activities	Pre-Lock down	Lock down 1	Unlock down 1	Lock down 2	Unlock down 2
Test done for Covid-19	22694	222199	4989378	862340	10532074
Confirmed cases	519	9844	384697	29617	1072030
Recovered cases	40	1325	255978	10398	747698
Death cases	9	330	11729	962	18854
Active cases	470	8659	202107	26916	507585
Positive cases (%)	2.29	4.23	6.42	3.61	8.47
Recovery cases (%)	7.71	13.17	61.36	29.42	66.85
Death cases (%)	1.73	3.27	2.98	3.25	2.18
Infection (%)	0.43	8.56	468.13	33.02	1353.48

We draw the following findings while taking into consideration that the numerically build models provide only with preliminary estimations in order to get needed “break widths”. In such a location with a high carrying capacity, it's indeed difficult to establish a break. A consistent control program creates to some degree more modest breakdown widths, hence chance of building a breakdown at a more prominent populace thickness than like "one-time" work for producing a breakdown.
This work suggests that infectious communicable diseases must be seen as socio-spatial processes featuring complicated geographies. Analysing the spatial dispersion of infectious illness in contemporary civilizations is made easier by taking into account the many concepts of space throughout which an epidemic unfolds [14].

Modelling Approach:
We suppose the community consists of just two populations that interact: infective susceptible, as well as recovered represented by $I(x,t)$, $S(x,t)$ and R. Nevertheless, I and S then were functions of both space variable x and thus time variable. We simulate the spatial dispersal of I and S using simple diffusion, initially assuming that infectives as well as susceptible have the same diffusion coefficient D. As previously stated, the shift from susceptible towards infective is proportional to rSI, where r is a constant parameter. This form rS denotes the number of susceptible individuals infected by each infectious agent. The parameter r quantifies the disease's ability to spread from infectives to susceptible.

We suppose that infectives get a disease-induced risk of dying aI; $1/a$ is the infective life expectancy, and m is recovery rate. With some of these assumptions, the fundamental model process for disease genesis and geographic distribution is formed.

$$\frac{\partial S(x,t)}{\partial t} = -rSR + D\nabla^2 S$$

$$\frac{\partial I(x,t)}{\partial t} = rSR - aI + D\nabla^2 I$$

$$\frac{\partial R(x,t)}{\partial t} = aI - mR + D\nabla^2 R$$

where a, r, m and D are positive constants. We exclusively explore the one-dimensional problem now; the findings of a two-dimensional investigation will be presented later.

Numerical Results:
PLD: Pre-Lock down
At outbreak stage, the Government of India (GoI) and thus the scientific community planned to adopt COVID-19 infection cure measures across India. The Indian prime Minister sought a state-wide voluntary community curfew on March 22, 2020, to ensure the whole users understand of COVID-19.

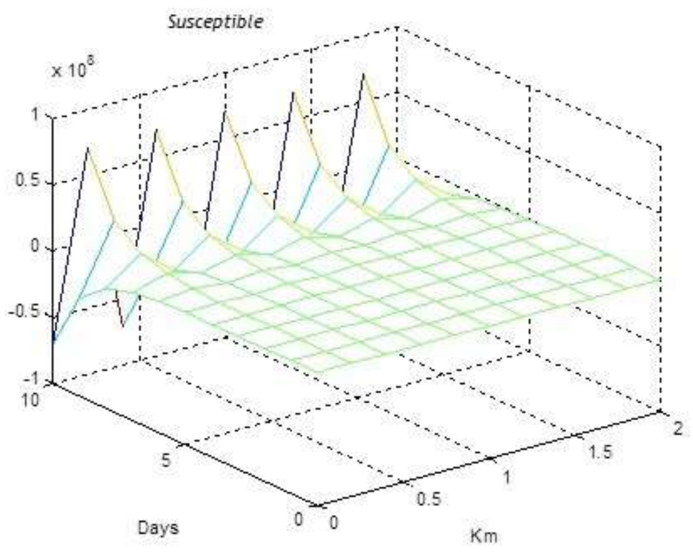

Figure 2a: *Susceptible computed at Pre-Lock down with respect to days and distance*

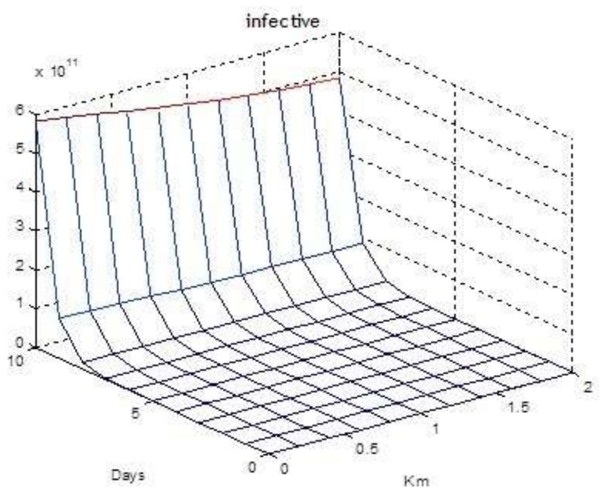

Figure 2b: *Infective computed at Pre-Lock down with respect to days and distance*

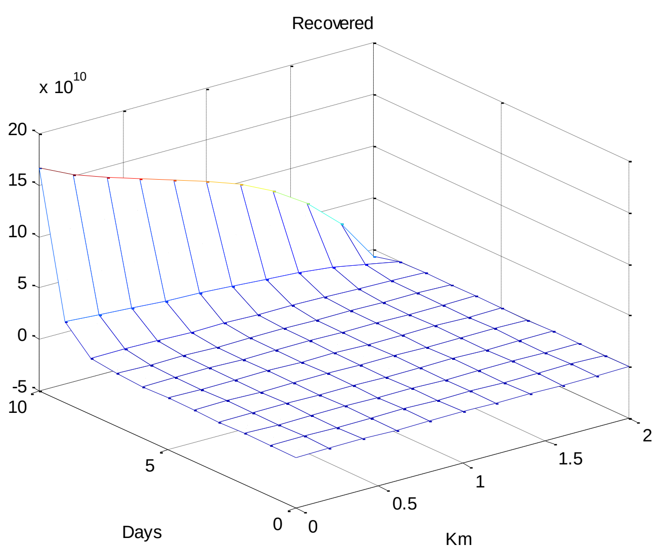

Figure 2c: *Recovered computed at with respect to days and distance*

Figure 2 a, b and c: Spatio-temporal representation of susceptible, invectives and recovered cases in Pre-Lock Down period. In this period, as no curfew was imposed, most of the population was susceptible and thus becoming infective at a higher rate, however the recovery rate was too slow due to no proper therapeutic intervention.

LD1: Lock down 1

The GoI started a synchronised national lockdown (LD) phase 1.0 (LD1.0) for 3 weeks on March 25, 2020, and further every single service was halted for saving necessary ones. Other preventative measures, like as wearing masks as well as gloves, applying sanitizers, keeping social distance as well as restricting large crowds, have also been applied throughout the country, or the incidence of illnesses decreased dramatically during LD1.0.

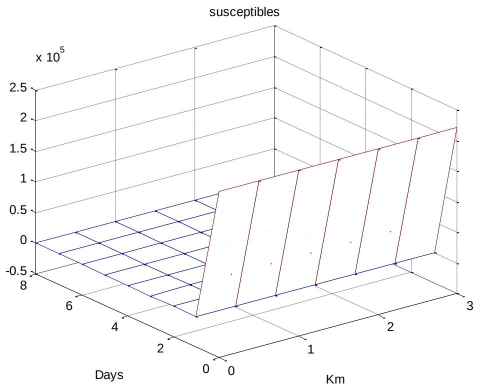

Figure 3a: *Susceptible computed at Lock down 1 with respect to days and distance*

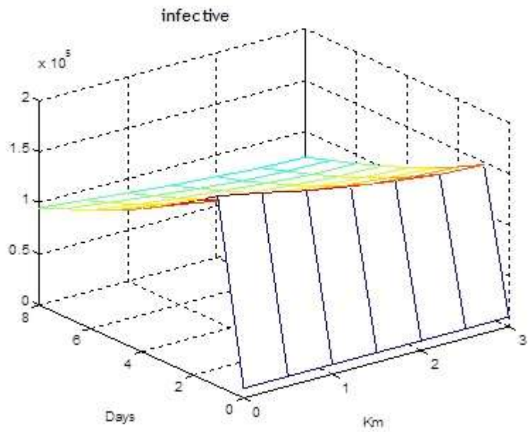

Figure 3b: *Infective computed at Lock down 1 with respect to days and distance*

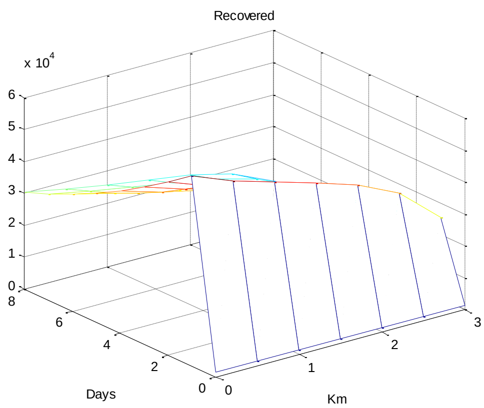

Figure 3c: *Recovered computed at with respect to days and distance*

Figure 3 a, b and c: Spatio-temporal representation of susceptible, invectives and recovered cases in Lock Down-1 period. In this period, as the movement of the entire population has been restricted along with other precautionary measures, the infection rate become slower and recovery rate a little higher, while the population is still somehow susceptible to COVID-19.

UD1: Unlock down 1

Based to the country's financial needs, the GoI notified several liberalisation inside “green” and “orange” areas by means of both the conditionally recommencement of facilities on June 1, 2020, and yet this resuming phase became “Unlock (UL) phase 1.0”. (UL1.0).

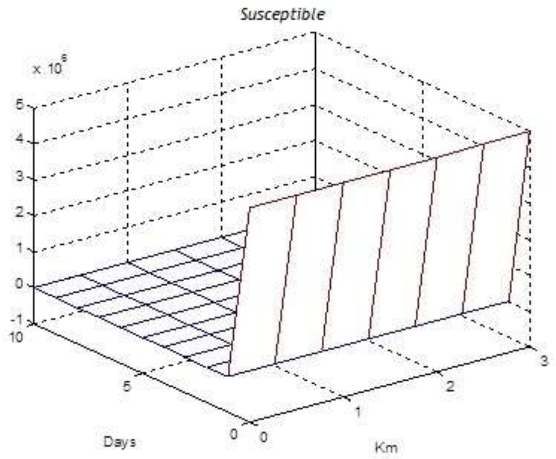

Figure 4a: *Susceptible computed at Un Lock down 1 with respect to days and distance*

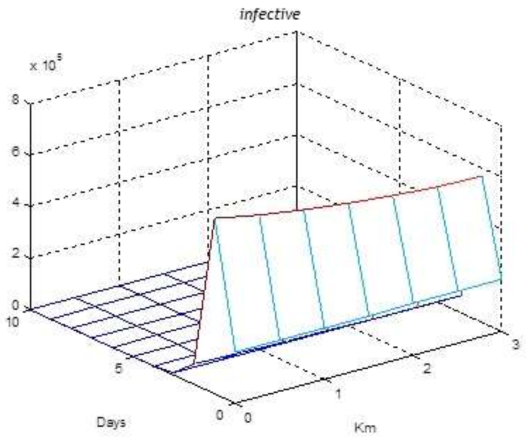

Figure 4b: *Infective computed at Un Lock down 1 with respect to days and distance*

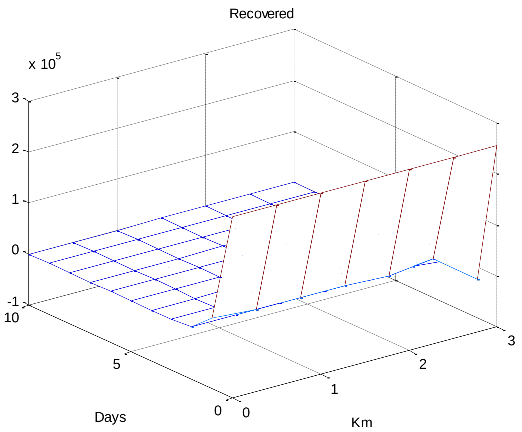

Figure 4b: *Recovered computed at Un Lock down 1 with respect to days and distance*

Figure 4a, b, c: Spatio-temporal representation of susceptible, invectives and recovered cases in Un-Lockdown-1. Infections expanded fast during this time period due to removal of regional travel restrictions and reopening of marketplaces, commercial place of work, factories, sacred institutions, and so on. and also, the susceptible rate. However, the recovery rate is at fine pace due to the therapeutic interventions (vaccinations).

LD2: Lock down 2

Upon that request of state governments and certain other GoI advisory groups, GoI prolonged LD term to LD2.0 for an additional 19 days on April 15, 2020. To combat the COVID-19 epidemic, LD2.0 was enforced under DM ACT-[Disaster Management Act of 2005]. This Act empowered GoI should precede the required steps for properly managing the nation's economic disaster situation via cooperating with national/state authorities and international organisations.

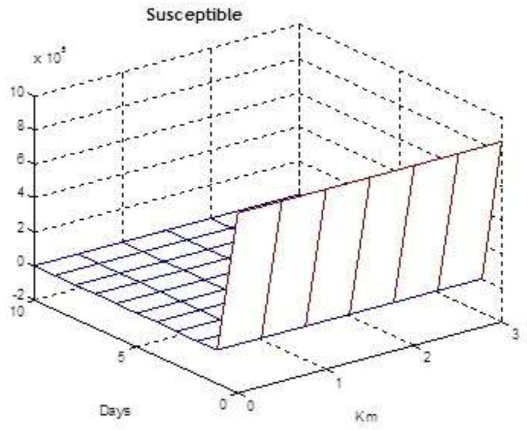

Figure 5a: Susceptible *computed at Lock down 2 with respect to days and distance*

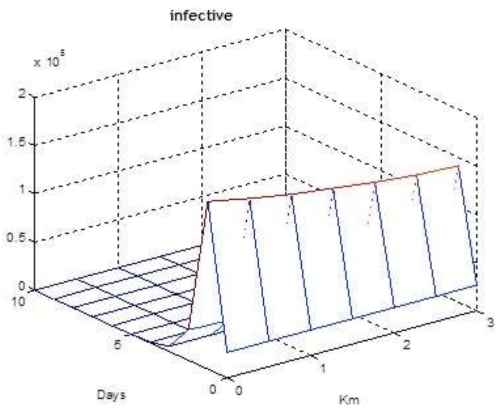

Figure 5b: Infective *computed at Lock down 2 with respect to days and distance'*

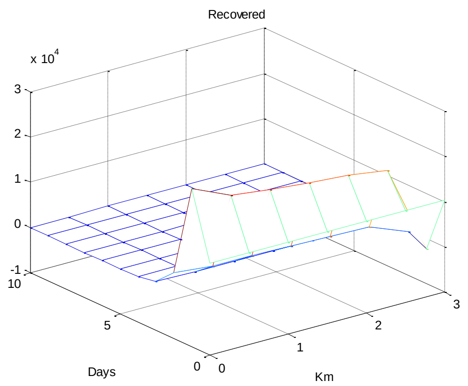

Figure 5c: Recovered *computed at Lock down 2 with respect to days and distance*

Figure 5 a, b and c describe the spatio-temporal representation of susceptible, invectives and recovered cases in lock Down-2. In this period, the recovery rate is little higher due to more than half of the population got their vaccinations, extra precautionary measures are being taken so the infective rate is lower and as the movement is restricted, the rate of susceptibility is also low.

Conclusion:

Humans want to know how much an epidemic may extend from its beginning to its finish, and we all want to look at the intensity of its infectious effect in locations very far from the origin. Till now, adding a spatial dimension to an applied infectious disease model has been regarded as a difficult technical insert that should only be addressed when absolutely necessary. This work is simple to comprehend and enables for the simulation of epidemic transmission in India.
Leading to frequent infections, the World Health Organization formally declared COVID-19 pandemic on March 11, 2020. COVID-19 instances in India have been rigorously examined in this study all through pre-lockdown (PLD), lockdown (LD), as well as un-lockdown (UL) stages.

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