

Risk Assessment Model: Roadmap to Develop Kolkata into a Smart City

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Abstract

Risk assessment is an analytical instrument used to measure a person's likelihood of certain diseases and disorders by quantitative risk factors in health (such as age, weight, living condition, literacy, the family history of a disease, etc.). A risk assessment model is a combined effort to identify and analyse potential events that can adversely affect individuals, assets, and the environment. Since times immemorial, infectious diseases have been the leading cause of widespread mortality globally. New ones are materializing, and old ones are resurging. Early identification of infectious disease and evaluating the risk factors are essential first steps towards executing successful disease intervention and planning control measures—various air-borne diseases like influenza, chickenpox, COVID-19, etc. are candidates for such models. By customizing the risk assessment model for Kolkata, we will monitor the factors responsible for the growth and spread of diseases. The current paper aims to focus on risk assessment based on the aggregation of various factors relevant to the prediction of disease transmission (RAAPDT).

Keywords: Risk Assessment, Early Identification, Kolkata, Pandemic/Epidemic

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1. Introduction

Epidemics or Pandemics are a public health emergency at the international level where the lives and livelihoods of millions are at stake. Today experts have developed numerous models with different hierarchies that may be an Artificial Intelligence-based Algorithm, Machine Learning Methods, Statistical Modelling, or mathematical calculations based disease forecasting model. The lessons we have learned from current lockdown in different countries are that it is difficult to sustain until the disease

is eradicated (91). Though for their efficacy, these models need to integrate information right from block or local levels of each constituency as successful prevention of an epidemic depends upon community behavior at large. The role of governments, in-flow, and outflow of information through trustworthy and organized channels are instrumental in contact tracing and isolation of suspected infected individuals. The social and emotional behavior of different communities plays a vital role in a developing multicultural economy like India. Health decision policymakers require models that integrate various perspectives, through timely and speedy dissemination of findings with different stakeholders (117).

2. Need for an early warning system for on-time prevention & control

The role of climate in the dispersion of infectious diseases is substantiated with empirical evidence, leading to the escalation of mortality and morbidity in developing countries. (16). Such diseases may reproduce at a faster rate to turn into an epidemic under the influence of climatic changes, promoting higher transmission rates: the rising requirement for early warning operational illness. It is only recently that inexpensive and open data and analytical methods have become popular, so EWS (Early Warning System) is evolving at a relatively early stage. New studies are now being conducted at a swift pace. There was no consensus on good practice in developing predictive models or measuring their accuracy and lead time. As a result, the effectiveness of current models is also hard to assess. Most research projects had relatively small funding and were therefore not conducted outside the original field of study (in this case, we consider Kolkata) (45; 46).

To deal with the outbreak of an epidemic, doctors need an early warning with sufficient time to plan the control measures. The purpose of an early warning system is to predict the upcoming development of disease case numbers, so that the health care professionals get adequate time to deal with unexpectedly high (or low) affected patients (27). Generally, it proves to be more effective in health services when it predicts case numbers, two to six months in advance, and facilitating planned actions when the risk of disease may increase (92). Long-term prediction is essential when calculated control of diseases is the objective (such as WHO's Onchocerciasis Control Programme to decrease Onchocerciasis or river blindness in parts of West Africa) (105). The business sectors also need proper planning to save the economies of the respective nations from crashing (77). It becomes possible only after having enough records for an evident understanding of the disease transmission dynamics (e.g. investigating the interaction between childhood diseases using data dating back to 1904 (139). In the case of infectious diseases (especially the vector-borne diseases), the predominant determinants would be spatial and temporal changes in environmental situations (27). Pollen grains transmitted through the air may also serve as a vector for airborne infections (109). The role of climate in the dispersion of infectious diseases is substantiated with empirical evidence, leading to the escalation of mortality and morbidity in developing countries. (16). Such diseases may reproduce at a faster rate to turn into an epidemic under the influence of climatic changes, promoting higher transmission rates: the rising requirement for early warning operational illness. It is only recently that inexpensive and open data and analytical methods have become popular, so EWS (Early Warning System) is evolving at a relatively early stage. New studies are now being conducted at a swift pace. There was no consensus on good practice in developing

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3. Airborne viral diseases

Pathogens transmitted through the air over period and distance by minor particles can give rise to airborne infections (118). These diseases spread when clumps of infectious agents are discharged into the air through sneezing, coughing, vomiting, spitting, talking, dust, or wheezing. These microorganisms cause diseases after entering the human or animal body through different respiratory passageways. Airborne pathogens, also known as allergens, can cause inflammation and irritation of the nose, mouth, sinuses, and lungs. It triggers by inhalation of allergens, which on entering affect the respiratory system of a person or, in some cases, whole body (8; 114; 76; 116). These diseases typically occur through the respiratory system with an agent present in the aerosol. Environmental factors encompass the potency of airborne disease transmission; the most noticeable factors being relative humidity and temperature (126; 106; 32). Some candidate diseases are - influenza, chickenpox, mumps, measles, and tuberculosis.

4. Elements rudimentary for transmission of infectious disease

1. Sources of infectious agents - Different vectors of infectious diseases (22; 10) found in human sources, spread either by coughing or sneezing. However, abiotic factors, like mist, dust, or aerosols, also play a significant role in the communication of infectious agents. The host, who may either be a patient (135; 21), or even health-care personnel (145), may either be in the incubation stage or the symptomatic stage or even be chronically colonized by the pathogen. Transmission may also occur from an animal to a human body, where the animal plays the role of the primary host, such as Fasciolosis (34).

2. Susceptible host - Infection is a consequence of a complicated relationship between disease-causing pathogens and its conceivable host. According to Osterholm et al. (2015, 2012) (97; 98), the severity of the disease caused, and its occurrence is directly related to the host organism. There are several possible outcomes following the susceptibility to a pathogen. Some become severely ill after getting exposed, while others show no symptoms, whereas some become permanently colonized with the pathogens while remaining asymptomatic. There are chances of an increase in severity with aging and the presence of underlying diseases in the host body (130; 58).

3. Virulent pathogens- Virulence of a pathogen is the ability of microbes to cause damage to the host. Virulent pathogens can be bacteria as well as viruses. Virulence can help understand the severity of the infection. The pathogen virulence can vary considerably over space and time (131). This variation can be density-dependent or may be due to seasonal variation shifts. Another study shows that when pathogens spread through a naive host population, the virulence rate increases (104).

4. Environmental and Social Components - Environmental factors like water supply, sanitation facilities, food, and climate, play an essential role in the spread of communicable diseases that can cause epidemics. (World Health Organization. 2005). Pavlovsky was one of the first researchers to study the interrelated components of disease occurrence in microclimate, flora, and fauna (102). As most developing infections are zoonotic, scientists are mainly keen to better understand the animal reservoir as a source of infectious diseases and how animal pathogens spill over into the human population and spread throughout the world (43).

5. Modes of transmission

Various types of pathogens can induce infection. The modes of transmission differ based on the category of an organism. Some are transmitted through infectious agents, whereas some through bodily fluids. Influenza virus transmits through contact, by which fomites can cause the direct or indirect transfer of infectious secretions. The respiratory fluids travel through the air and deposit onto

mucous membranes or aerosols; the droplets suspended in the air can scatter over long distances. They have a high risk of being inhaled (146; 13; 127; 128). The risk of infective droplets depositing on the mucous membrane (mouth or nose) or conjunctiva (eyes) is exceptionally high (26; 18). Another possible transmission of droplets can occur through fomites (dishes, doorknobs, stethoscope, and thermometer). Transmission through aerosol (< 5µm in diameter) is more dangerous as they stay in the air for long durations and can transfer to others over distances higher than 1 m. There are mostly three principal routes through which transmission occurs. These are

1. Contact transmission - it is further divided into two subtypes:

a. Direct contact transmission - this mode of transmission takes place when the pathogen is directly transmitted from one infected person to another without any intermediate agent.

b. Indirect contact transmission occurs when the pathogen is transmitted from one infected person to another with the help of an intermediate agent (which may be both biotic and abiotic).

2. Droplet transmission is a type of contact transmission where the disease is transmitted when respiratory droplets carrying harmful pathogens get carried from the respiratory tract of an infected individual to the mucosal surface of a vulnerable individual. These respiratory droplets are generated during coughing, sneezing, or even talking of an infected individual.

3. Airborne transmission occurs when the infectious agents are circulated over long distances by air currents, which can then be inhaled in by any susceptible host, thus acquiring the infection.

6. Current preparedness of disease management in India

The coronavirus disaster has emphasized India's willingness to cope with these devastating times- with its high urban density, lack of hygiene and sanitation, and, more importantly, weak treatment capability. West Bengal and North East Indian regions share several international borders with Coronavirus infected countries like China, Myanmar, Nepal, and Bhutan. Although the borders are under control, there are chances of existing unreported cases. Also, as per the last Census in 2011, an estimated 220 thousand people have migrated from West Bengal to other states in search of work, and these estimates have exponentially grown over the last decade. West Bengal ranks 4th in terms of outbound migrant labourers, after the states of Uttar Pradesh, Bihar, and Rajasthan, especially from the districts of Malda, Burdwan, Nadia, Hooghly, and Murshidabad. The fact that a vast majority of these migrants are seasonal labourers and their preferred destinations are Maharashtra, Delhi, Kerala, and Karnataka (the most intensely infected states in India). They pose a severe threat of COVID-19

transmission given the uncontrolled return of these migrants to West Bengal induced by panic in the pandemic situation (84).

The rapid urbanization that has increased mobility and led to higher density has raised new challenges to sanitation and healthcare. Other environmental, demographic, and socio-economic factors put India at high risk for communicable diseases, including its large population that facilitates transmission of disease and changes in agricultural practices that introduce zoonotic pathogens (68).

7. Indian urban agglomerations

Opportunities motivate individuals to shift to greener pastures, thus explaining the rate of increase in migration from rural to urban areas; this transit is more prominent in South Asia (36). It leads to an entangled mess of problems despite opportunities and requires resources in finance, skilled labour, planning, sustainability issues, and nonetheless, socially empowered leadership. This migration generates clusters of urban slums that are unorganized, deprived of basic city amenities, and impoverished. Urban settlements are the epicentre of power, finance, and infrastructure development (84; 119). The critical policy decisions must focus on civic amenities, housing, land-use, healthcare facilities, educational facilities, industry, and environment.

Kolkata, also famous as India's cultural capital, has a population growing at an increasing rate in suburbs and fringes as the core is saturated (88). It creates a discriminative distribution of wealth and civic amenities, and Kolkata also suffers from the menace of exclusion, maintaining a loop of spatial poverty. This load on infrastructure reduces a city's potential to promote wellness and happiness among citizens. Thus Kolkata needs to be more inclusive and sustainable in its outlook for expansion and up-gradation as a smart city.

8. Smart city and hybrid city

A smart city is a city that uses a variety of internet sensors to gather data and then use it to manage properties, resources, and services efficiently. These include data collected from residents, transport facilities analysed and assessed power plants, power stations, water systems, waste management, crime prevention, information systems, schools, books, hospitals, and other services. They provide information obtained from public services (90).

As proposed by Norbert Streitz (2019) (123), a Hybrid City is a modern city with its citizens and physical structures, and a virtual alternative city of citizens and equivalents. However, the match between real and virtual entities will not be complete. The addition of a "traditional" city to an added digital city leads to what we

call a "hybrid city." The paper's objective is to transition a traditional city into a "smart city" (123).

8.1. Hybrid city- a conglomeration of small towns

We hope to deliver a new model of growth, a hybrid approach incorporating the best of rural and urban attributes. This model will inspire us to look beyond town and rethink our urban centres as we plan tomorrow's cities. It will suggest subduing the inferno and spreading pressures within megacities by bringing the countryside in, as it were. The hybrid city would be a sustainable community that focuses on citizen participation, equality, environmental soundness, and economic diversity. The hybrid city seeks to combine cultural sophistication, friendliness, conservation, flexibility in energy, sense of scale, location and self-reliance, and a sense of communion with the best qualities of cities like diversity, density, creativity, economic mobility and access to the means of human growth.

9. Kolkata

Kolkata, the capital city of West Bengal, is the dominant urban centre of eastern India. Formerly known as Calcutta, the city was chosen to be the capital of British India and hence was designed by the colonial British in the manner of a stately European capital (78; 9). However, it has now turned into one of the most overpopulated and impoverished regions of India. It has a land area of 205.00 square kilometres (87).

9.1. Demographics

The demographic details are as follows:

Population

Following the Urban Agglomeration (UA) of UN World Population Prospects, Kolkata has a population of 14.8 million (1.48 crores) in 2020 (23, 24), making it the third most crucial metropolitan city in India. According to Haque, I., Mehta, S., & Kumar, A. (2019) (54), "the administrative jurisdictions of Kolkata Urban Agglomeration (KUA) and Kolkata city district (Kolkata Municipal Corporation / KMC; wards: 141; population: 4.5 million), covers an area of 1,886.67 sq. km and 205 sq.km, respectively." The provisional reports of Census 2011 state that about 4.9 million people, which comprise about one-third of the total population of Kolkata (70; 71), consist of slum dwellers residing in 2,011 3,500 unregistered slums in 141 various wards of the city (11). The population density of Kolkata is 24000 per square kilometres spread over 185 square kilometres, with slum density being 2812 people per hectare (25).

Literacy

On the other hand, the literacy rate of Kolkata hovering at 87.14% is better than the national average of 74%.

Age and Sex-ratio

The sex-ratio of Kolkata currently consists of 899 females per 1000 males, which is far below the national ratio of 940 females per 1000 males. The given population pyramid (Fig. 1) represents the gender difference between males and females of different age groups. The lowest population is in the age group of 70-80 years. The highest population is represented by the age group of 20-40 years.

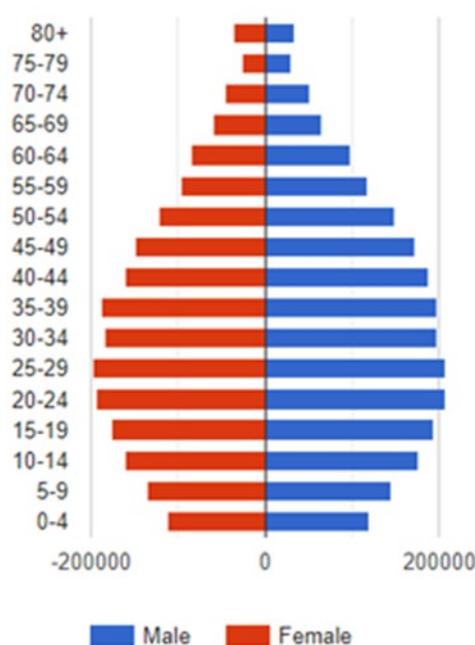


Figure 1. Population Dynamics of Kolkata, Census (2011).

Ethnic Groups

The dominant religion of the city is Hinduism (77.68%), followed by Islam (20.27%) and Christianity (0.88%). Other minor religions include Buddhism, Jainism, and Sikhism. Bengalis represent the largest community in Kolkata, with Biharis, Marwaris, and Punjabis, constituting the other minor communities.

Administration and Municipal Services

The city is a part of the Kolkata Metropolitan District (constructed to supervise planning and development on a regional basis). It falls under the jurisdiction of the Kolkata Municipal Corporation (KMC).

Kolkata receives its main filtered water supply (260 million gallons daily) from the waterworks in Palta, along with a few other water treatment plants and hundreds of other major and minor dams. Additionally, unfiltered water is also supplied regularly for washing the city

streets and the fire brigade. This water is often used by the slum dwellers for drinking purposes and is one of the major causes of the prevalence of Cholera during the summer months. The garbage disposal system and maintenance of the sewers by the KMC is also unsatisfactory.

10. State of disease management of Kolkata

Kolkata has about 48 Government hospitals and 366 private medical establishments, consisting of more than 27,000 beds. It results in about 60 beds on average per every 10,000 people in the city. Proper control measures are also taken by the KMC to tackle the common infectious diseases in the city (Table 1). Apart from these, routine immunizations are also provided by various health centres for many other diseases like Diphtheria, Tetanus, Whooping cough, Measles & Hepatitis - B.

Table: 1. Treatments centres and control measures issued by KMC to deal with infectious diseases in Kolkata (Kolkata Municipal Corporation, 2020) (72)

Sl. No.	Diseases	Control Measures	Treatment Centres
1.	Malaria	1) Early diagnosis and prompt treatment 2) Vector Control + Information Education and Communication (IEC) for improved Artemisinin Combination Therapy (ACT)	60 Clinics (in general) 3 Malaria clinics
2.	Tuberculosis	1) Early diagnosis and prompt treatment by Sputum Microscopy. 2) Directly Observed Treatment Short-course (DOTS) program. 3) An awareness campaign for the prevention and protection of the mass.	52 Microscopy centres 10 X-Ray centres 92 Drugs distribution centres

3.	Leprosy	1) Early detection through tests 2) Generation of awareness to report any suspicious skin lesions. 3) Multi-Drug Therapy (MDT) as per the routine control program.	59 treatment centres
4.	Gastroenteritis	1) Check on potable water by means of sample analysis 2) Early treatment of affected through medicines and Oral Rehydration Solution (ORS)	89 treatment centres
5.	Poliomyelitis	1) Routine immunization Programs. 2) Intensified Pulse Polio Immunization (IPPI) Program.	98 centres for routine immunization 1378 booths for IPPI Mobile teams for house-to-house visits.
6.	Cough, cold, fever, Influenza and Diarrhoea	Examination, Diagnosis, and treatment	26 dispensaries

11. Modelling and forecasting of infectious diseases

11.1. Epidemiology modelling strategy

The methodology used can vary depending on the intent of the research, how adequately a disease's epidemiology is comprehended, the percentage and characteristic of available data, and the modeller's context and experience. Depending on their treatment of variation, chance, uncertainty, and time, it can be divided into numerous groups (47).

- Population dynamic models: a study of modifications in the arrangement of population

- Risk models: describes the threat of introduction of disease into a population qualitatively
- Analytical models: utilized to recognize federations amongst the circumstance of disease and risk factors
- Economic models: considering monetary values and allocation of reserves (55).

Based on the flu-forecasting landscape (96; 29), there are four types of disease forecasting models:

1. Mechanistic Model - These are models based on differential equation algorithms. They describe the transmission pattern of an epidemic (132).
2. Agent-based Model - This type of model creates a simulated population that mimics a real population. It uses demographic information from various online databases to approximate disease transmission through such a population (50).
3. The machine learning or regression model follows the history of epidemic outbreaks and uses that pattern to predict future epidemics. These models employ various approaches like clustering statistical time series (121), non-parametric approaches (14), or regularised regression (5).
4. Data assimilation or Dynamic Model - This type of modelling approach involves implanting a mechanistic model into a probabilistic model (37). It enables explicit modelling of both the pattern of disease transmission along with observational noise (100). Thus, this modelling approach combines both the parametric and random uncertainties observed in the models mentioned above.

11.2. Climatic and non-climatic risk factors in disease forecasting

The identification process of both climate and non-climatic risk factors offers a crucial insight into the design of the Early Warning System (EWS). Many studies classify environmental risk factors associated with climatic vulnerabilities (143). Two primary modelling methods are available: statistical and biological. The statistical models are used to estimate the association between forecaster variables (e.g., climate) and thereby study the chance of disease occurrence. Biological models aim at providing an automatic process in which climate impacts pathogens and vector population dynamics. Most of the past research used locality-based statistical analysis and vector distributions for particular historical disease steps. Although biodiversity models may provide greater insight into mechanisms that lead to variations in the impact of diseases, they need to inform the climate's

impact on all aspects of pathogens and vector dynamics. It has led to the rare use of these models (107). Irrespective of the modelling methodology, it would be irresponsible to ignore the impact of non-climatic factors. These include indicators of population susceptibility to outbreaks of disease, such as low immunity (for example, malaria), high HIV prevalence, malnutrition, drug, and insecticide resistance. Failure to assimilate such influences may lead to incorrectly attributed variations in the incidence of disease due to climate effects and reduced predictive precision (142).

12. Pre-existing models of disease forecasting

Disease Forecasting is an approach to predicting the outbreak of an epidemic. A Disease Forecasting model provides information beforehand about the disease outbreak's geographical extent and its expected time of onset (129). Early identification of an infectious disease contributes immensely towards executing successful disease intervention methods, efficient resource allocation, and planning control measures and saving more lives (99).

Disease forecasting models are developed by the combined efforts of computer science specialists and the mathematical community. These models propose an investigation of relevant literature describing diseases and their physiological phenomena (92). One such model formulated using differential equations is the SIR Model.

Compartmental models abridge the statistical modelling of infectious diseases. The population is reallocated by marking regions-for example, S, I, or R (Susceptible, Infectious, or Recovered). People can make changes between compartments. Traditionally, the directive of the labels indicates the flow arrangements between the compartments; for example, SEIS means susceptible, exposed, infectious, and susceptible.

12.1. SIR model of disease forecasting

SIR stands for Susceptible-Infected-Removed. The classical Kermack-Mckendrick SIR model has an executable working algorithm and has been used to describe the transmission of the COVID-19 virus pandemic (20). It is a mechanistic model that consists of both parametric and non-parametric methods (95).

The model formulates the following quadratic equations (138):

$$\frac{dS}{dt} = -\beta SI \quad (1)$$

$$\frac{dI}{dt} = \beta SI - \nu I \quad (2)$$

$$\frac{dR}{dt} = \nu I \quad (3)$$

$$R_e = \frac{S(0)\beta}{\nu} = \frac{S(0)b}{\nu N} = \frac{D\kappa\tau S(0)}{N} \quad (4)$$

Here, β is the rate of disease transmission, S is the number of individuals susceptible to be infected at time t, I is the number of infected individuals (both symptomatic and asymptomatic) at time t, R is the number of recovered individuals at time t and ν is the recovery rate. Hence, the term βSI is the number of newly infected individuals per unit time t, corresponding to a homogeneous interaction between the infected and susceptible populations. Similarly, the term νI is the number of recovered individuals per unit time t.

The sum of the left-hand side of equations (1), (2), and (3) is the derivative of the total population size, and the sum of the right-hand sides is zero, and hence the total population size remains constant. Also, as it is evident that the recovered individuals are equal to the total population size, which is neither susceptible nor infected (over a time t), thus, it is mathematically depicted as $R(t) = N - S(t) - I(t)$.

Also, here, D is the duration of infection (thus, $D = 1/\nu$), N is the total population size, κ is the number of contacts (each with the ability of transmission) an infected individual has made per unit time; this parameter is independent of N (thus, $\kappa S/N$ of these contacts have susceptible individuals). τ is the fraction of contacts which results in transmission; hence it is called the transmissibility parameter, and R_e is the effective reproductive number. Thus, here $\beta = b/N$ where $b = \kappa\tau$.

Here, the actual reproductive number equates the time-span of the infection with the number of susceptible individuals that an infected individual has contacted, per unit time, and the transmissibility (i.e., the transmission rate). It evaluates the number of new infections; each infected individual can cause at the beginning of the outbreak. R_e is thus the degree of pathogen fitness. The SIR model becomes a SIRS, where the recovery does not give long term immunity, and the individual can become susceptible again. SIR model becomes Susceptible, Infectious, and Recovered.

12.2. SIS model of disease forecasting (susceptible, infectious & susceptible)

The SIS model explains the spread of a solitary transmissible disease in a susceptible population of size N. Transmission of the pathogen arises when infectious hosts communicate the pathogen to healthy vulnerable individuals (115). Here, S stands for Susceptible, I for infected. It deals with the fact that someone who was affected by a viral disease and later got cured can reencounter the same disease in the future. For example, individuals highly symptomatic with regular common colds and intermittent fever have weak immunity in the long run. These infections do not provide long term resistance after initial recovery, thus making them susceptible again. In this model, at any time, the susceptible and infected people are taken into consideration, which makes up the whole population. A

logistic equation rules the dynamics of the infection. The SIS model allows us to analyse how the infection continues to spread (and is possibly reintroduced) over time. The SIR model is more appropriate to the disease awareness framework that the paper wants to implement (75). The reason why SIS models are selected above SIR models is that the SIS model demonstrates the persistence of the disease within the population over a long period when individuals are re-infected, and the model maintains endogenous equilibrium. The SIS model studies diseases where the extinguished infection resurfaces in a community, and the intensity of these reintroductions is looked into (51).

12.3. TDEFSI model of disease forecasting

Theory Guided Deep Learning Based on Synthetic Knowledge Epidemic Forecasting (TDEFSI) (137), is a disease forecasting system that combines the benefits of deep neural set-ups and high-resolution disease process simulations across networks. TDEFSI produces precise, high-resolution spatiotemporal predictions using data from time series of low resolution. During the training process, TDEFSI uses high-resolution epidemic simulations to identify patterns in urban-inherent spatial and community heterogeneity as one component of training statistics. A two-branch recurrent model of the neural network is trained to take low-resolution observations both within and between seasons as features and produce high-resolution, detailed forecasts. The resulting forecasts are influenced by the diverse financial, demographic, and geographic characteristics of different urban regions and mathematical disease propagation theories through networks.

12.4. Bayesian Model of disease forecasting

Bayesian Model is a predictive and intuitive- statistical tool based on the theory of probability to identify the uncertainties in a particular model, in which probability expresses a degree of credence or the strength of our faith in the unit occurrence of a proposition. Bayesian statistical methods use the Bayes theorem to measure and update probabilities after new data gets collected. This approach uses sequential analytical methods to integrate previous experiments' effects into the design of the next experiment.

Bayes Theorem is stated mathematically as:

$$P(A | B) = \frac{P(B | A) P(A)}{P(B)}$$

Where A and B are events and P(B) is not equal to zero.

Most Bayesian methods assess sophisticated calculations, including the utilization of techniques for simulation. It provides a natural and principled way to

combine prior information with data in a robust theoretical decision framework. It offers data-based and reliable inferences, without depending on exponential approximation. There are disadvantages to this model too. It may produce successive distributions that are heavily influenced by priors. It often generates additional computational costs, particularly in models with several parameters. We may apply the Bayesian model described above to the various diseases forecasting in Kolkata (63).

13. Case Study: Coronavirus (Covid19)

Coronavirus is a human-infected virus, usually causing an Upper Respiratory Infection (URI). It was first characterized in the 1960s. The virus spreads through coughing, sneezing, close personal contact with virus-contaminated objects, etc. Human coronavirus is known to cause acute respiratory syndrome, MERS Cov (beta coronavirus causing Middle East respiratory syndrome), SARS Cov (beta coronavirus causing severe acute respiratory syndrome), and 2019 Novel Coronavirus (2019-nCov) which started in Wuhan, China (64).

Timeline of Covid-19(Adapted from COVID-19 Dashboard by the Centre for Systems Science and Engineering (CSSE), 2020) (32)

- Coronavirus Disease 2019 (Covid-19), caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS Cov-2), was identified first in December 2019 in Wuhan, China.
- Gradually, the virus spread over all of China's provinces and over 150 other countries in Asia, Europe, North America, South America, Africa, and Oceania.
- SARS-CoV-2 was published as a Public Health Emergency of International Concern by the WHO on 30 January 2020.
- On 11 March 2020, it was declared as a pandemic by WHO.
- By 20 May 2020, there had been 4,897,567 total confirmed cases of SARS-CoV-2 infection in the ongoing pandemic

14. Customizing disease forecasting model for smart Kolkata

Any information or data acquired needs to be quantitatively or qualitatively analysed to understand it in a prima facie broader sense and utilize it later for implementation in a project, either in vitro or in vivo. Before diving into data analytics, it is crucial to understand the main differences between qualitative and

quantitative data. Quantitative data are information on quantity, and therefore the number and definition of qualitative data and the phenomena which can be detected but not measured, such as language, are descriptive. Whereas, the Qualitative data focuses on a multi-method approach that requires an understanding of its fundamentals. It means that qualitative scientists study things in their natural environments and try to elucidate phenomena (113).

15. Identifying hotspots

In epidemiology of infectious diseases, the term "hotspot" signifies "red flag" regions of escalated disease burden or high order of transmission (74). In the case of Malaria, it helps to identify clusters with increased incidence (7), which might either be a district (122) or even a country (59). There are various types of hotspots, defined as:

1. Transmission hotspot – a region of elevated efficiency of transmission (4).
2. Emergence hotspot – a region with a high frequency of emergence or re-emergence of drug-resistant strains (103).
3. Burden hotspot – a region with increased occurrence or prevalence of a disease or a geographic collection of cases (6).

Emerging infectious diseases (EIDs) are a noteworthy problem for public health and global economies (85). Various efforts to comprehend EID emergence patterns have emphasised the fact that because of its rapid nucleotide substitution rates, negligible mutation-proofreading ability, and hence elevated capacity to adapt to new hosts (140), viral pathogens (especially RNA viruses) are a significant threat (30).

Identifying hotspots provides a foundation for emerging a predictive model for the domains where new EIDs are most likely to originate. Regression results from surveys about socio-economic, ecological, and environmental correlates of EIDs (62) identify the regions where new EIDs are expected to emanate (emerging disease 'hotspots').

To identify a hotspot of infectious disease, knowing just about the causal pathogens is not enough. Factors that resulted in that pathogen being designated as an emerging disease, such as the climate, the chronological exposure of a pathogen within a human population, the increment distributions, the incremental frequency of incidence (or virulence), etc. (86).

16. Contact tracing

Contact tracing is a well-accepted method to control infectious diseases by attempting to detect cases more efficiently by following chains of infection (38). Its target is the identification and isolation of individuals who have been in contact with infectious or affected individuals

(69). It aims to set a target for the various control measures such as prophylactic vaccination (2) or pre-emptive culling (66), to combat the spread of the infection or even totally eradicate it (40), more efficiently. Contact tracing links the individual-level spread of infection to the network of potential transmission routes. The network is a very significant factor in contact tracing as it brings in to count the impact of social interaction, which can occur over a wide range of geographical distances, which in turn can determine the risk of infection (69).

Several types of contact tracing models exist, like models that consider randomly interacting models (61; 89) or network-based models that consider transmission pathways (53; 60). Detailed pairwise equations associated with these models can deliver a precise mechanistic understanding of human interactions' distributed nature (39). The pairwise correlation models provide a robust mechanism for capturing spatial effects by framing equations for the number of linked pairs instead of calculating just the number of single affected individuals, thus linking individual-level behaviour to population-level dynamics in times of epidemics (133; 42). It offers a systematic framework and can be easily parameterized using the existing data and formulates consequences based on the transmission network (39).

17. Rate of spread of diseases in a clustered population

The human-to-person contact networks establish the substrate along which communicable diseases spread. Most network-based studies of this spread concentrate on degree variations (the number of contacts and the number of individual contacts). However, other consequences, such as clustering, changes in infectiousness or vulnerability, or differences in the closeness of contact, may play an important role (82). Edge weights (measuring proximity or length of contacts) affect even if there are similarities between different edges. Besides, these effects can play a significant role in strengthening each other, with the more considerable influence of clustering when the community is maximally heterogeneous or when close connections are also densely clustered (82).

The disease spike is one of the most substantial concerns in an outbreak, and its severity and duration are critical for health care providers. Epidemic statistics are in the form of time-series such as $p(1), \dots, p(t), \dots, p(T)$, where $p(t)$ represents the number of current cases of infection reported in time t and T is the length of the epidemic season. The peak value is the highest value in the time series. In the framework of the epidemic, it corresponds to a high number of individuals that are newly infected in any given week during the epidemic season. Seasonal diseases, such as influenza, typically remain latent and display a dramatic increase in the number of cases only before the season starts. Emerging infectious diseases show a typical pattern of sharp rise.

18. Risk assessment based on aggregation of various factors relevant for prediction of disease transmission (RAAPDT)

Several methods are used to study the transmission of diseases. Perhaps the most crucial decision in building a model is how the population's interactions are portrayed (73). The efficacy of agent-based modelling lies in its dynamic functioning based on customization capacities in heterogeneous populations. Simulations based on fuzzy, complex logic are helpful in medical decision making as it is nearly improbable to objectify future human behaviour. Though fuzzy logic and Bayesian probabilities address different problems of uncertainty, probability theory predicts the frequency of occurrence or likelihood of an event, and fuzzy logic tries to find out /ascertain the presence of observation within a prior (approximately) defined set.

The current model is more descriptive and exploratory in perspective, keeping different logical analysis models in perspective. It comprises synthetic population mapping based on specific attributes (136), contact tracing, and hotspot marking. Almost all sophisticated strategies use agent-based models; each person's movements are tracked, as individuals in the same social cluster can infect each other. Usually, to build these models, significant capital and institutional support are needed (81).

18.1. Area-wise population density

Kolkata is approximately 205 square kilometres (54). North Kolkata is known for 19th-century architecture and narrow lanes, including areas such as Shyambazar, Shobhabazar, Chitpur, Cossipore, Baranagar, Sinthee, and Dum Dum. These places are mostly clustered and high population density zones. Central Kolkata is inclusive of government officials buildings (The West Bengal Secretariat, General Post Office, Reserve Bank of India, High Court, Lalbazar Police Headquarters, etc.) and close conglomerates of businesses and old markets (Burrabazar, Central Avenue, B.B.D.Bag, Esplanade and Strand Road). This area is densely populated and quite old. Whereas Park Street, which comprises thoroughfares such as Jawaharlal Nehru Road, Camac Street, Wood Street, Loudon Street, Shakespeare Sarani, and A. J. C. Bose Road, has a mixed density with mushrooming of both businesses, malls and residential apartments. South Kolkata is an urban high socio-economic locality (Ballygunge, Alipore, New Alipore, Lansdowne, Bhowanipore, Tollygunge, Jodhpur Park, Lake Gardens, Golf Green, Jadavpur, and Kasba) with medium to low density, in comparison with other localities. The two townships also situated in Kolkata Region are Salt Lake City (Bidhannagar) and Newtown, these townships have their municipalities and have low population density.

18.2. Age

It is imperative to know about the different age groups in Kolkata and control the future spread of airborne diseases. According to the census of West Bengal (2011), people in the age group (05-14) -20% and (40-49) -14% years are much more than the other age groups. The least population is in the age group (81 +). But nowadays, due to better medication, the population density of the age group 81 + is gradually increasing. Air pollution is a significant threat to children for both acute and chronic respiratory disorders. Children are more prone to airborne diseases due to their immature respiratory organs. The population density of the children of age group (5 to 14) is very high in Kolkata, so it is vital to monitor them in case of a pandemic. People in the age group above 81 + are also prone to such diseases due to weakened immunity. But it is advisory for all the age groups to be aware.

It may be suspected that in future pandemics, the younger (5-14) and the older people (81+) are more prone to infection, and so, proper monitoring is necessary.

18.3. Literacy

The literacy rate of a city is a parameter of utmost importance in devising a disease forecasting model to prevent the outbreak of an infectious disease in that city. The higher the literacy rate, the higher the standard of living, the better the chances of fighting an epidemic. A literate individual is more likely to have a job and a secure financial condition. Hence, it is more likely to be socially aware and have the means to follow the guidelines during an epidemic outbreak.

The literacy rate of Kolkata (as per Census 2011) is 87.14%, which is higher than the state (West Bengal) average of 77.08%. The male literacy percentage of the city ranks at 89.08%, whereas the female literacy ranks at about 83.79%.

For administrative purposes, KMC has divided Kolkata into 144 different wards. Out of these, wards 1-33 lie in the North of the city, and the average literacy rate of northern Kolkata is about 85.41% except for some wards like 23, 24, 29 and 32 covering the regions Pathuriaghata, Posta, Ultadanga and Kankurgachi, and Narkeldanga respectively, where the average literacy rate is around 72.68%. In central Kolkata, consisting of wards 34-65, the average literacy rate is about 83.33% (the zone with the lowest literacy rate in the entire city) except for the wards 36 and 60 covering the regions of Beliaghata, Sealdah, Rajabazar, and Park Circus. These wards have meagre literacy rates of 66.34% and 44.16%, respectively. South Kolkata, consisting of wards 66-141, on the other hand, has the highest literacy rate in the entire city with an average rate of around 88.79%, with the highest literate region being ward 96 with a literacy rate of about 96.57%.

In case of an epidemic outbreak, the city's central region would be more prone to getting affected by the disease and would contribute in spreading it further.

Simultaneously, the southern zone of Kolkata would be the least prone region within the city.

18.4. Sanitation

Hygiene and sanitation play the most significant role in controlling the spread of infection. Globally, about 8, 27, 000 people, in underdeveloped and developing countries, die because of poor sanitation and hygiene, every year (WHO) (141). Poor sanitary practices such as unsafe sewage disposal, lack of clean drinking water, open defecation, and usage of community washrooms (public toilets) perpetuate a vicious cycle of disease and poverty. Surveys suggest that more than 75% of Kolkata's slum dwellers do not have a personal supply of clean drinking water, and about 88% of them use public toilets (112). Adding to that is the unacceptable levels of the potability of the supplied drinking water (125). Additionally, a crowded living condition does not allow for proper sewage disposal systems to be built in the slums. Studies suggest a high rate of childhood diarrhoea in the various slums of the different municipal wards under the KMC (101).

i. Water Supply Management in Kolkata

Water and sanitation are the two most important criteria for a smart city as both give us an idea about poverty, economic growth, and sustainability. A water-smart city must combine urban planning and water management to create a green and robust infrastructure to cope with different challenges. It is designed to acquire meaningful and actionable data on flow rate, pressure, and distribution of the water (19).

The issue of water being priced is controversial due to its physical, political, and economic aspects. Rapid urbanization and population growth in many cities worldwide have contributed to scarcity and rising water costs (79). The Government of India (GoI) aims to cover the increasing number of homes with uninterrupted 24×7 water supply: piped-water supply with all metered household connections. The GOI initiated another 100 Smart Cities mission in 2015 to integrate city services, allow more effective use of scarce resources and, generally, improve residents' quality of life.

For a city to qualify as 'smart' in terms of water supply, it needs to build a 'smart and sustainable water network. Thus, it depends on how well municipal water utilities manage distribution networks with available resources, raise awareness of efficient use, provide safe water, manage leakage, and generate income. Kolkata currently faces a confusion of whether to choose a right path of valuing water or the typical path of not imposing any price on it (48). The highly unequal distribution of water in many parts of the city is due to the lack of infrastructure and weak financial conditions (65). The availability of water results in a change of population density; hence, it is an essential parameter for this model.

ii. The drainage system in Kolkata

The principal features of the existing drainage basin were laid out in the Master Plan of Calcutta Metropolitan District (1966-2000). It was prepared by CMPO concerning water supply, sewage, and drainage. Much of Kolkata's core city (93) is covered by a hybrid form of underground drainage network in which both sewage and storm water flow into the same conduit (83). The drainage is raised and eventually discharged into the tidal river through outfall channels further down to the east (94). Because of the city's unique physical characteristics (bowl-shaped), the centre is somewhat in depression, so that every drop of wastewater/rainwater needs pumping to relieve waterlogging (12). Hence due to waterlogging in different parts of the city, the spreading of disease is very common.

18.5. Social behaviour and habits of residents

Human behaviour plays a significant part in the spread of contagious infections (28). Hence, understanding the impact of behaviour on the spread of diseases can be crucial in enhancing control measures (44). The lockdown period during the Covid-19 pandemic and other epidemic breakouts over time has made it quite evident that in times of an epidemic outbreak with no significant pharmaceutical interventions, people tend to change their habits to avoid getting infected (49). Different non-pharmaceutical measures such as social distancing, closing schools and universities, and a ban on mass gatherings (31; 80) have significant impacts on human lives. Constant news updates about the spread of the disease and the numbers of affected and dead individuals also tend to make people follow hygiene more rigorously. Population mixing is also an essential factor in the spread of a viral disease. Information about social mixing is a significant parameter in devising intervention strategies, to control the spread of the disease, using social network epidemiology (108; 35).

In Kolkata, we see a variety of changes in people's behaviour and habits depending on their socio-economic status, level of literacy, and residence. In the case of the slum dwellers, consisting of about 33% of Kolkata's population, who generally belong to backward socio-economic classes and have a low literacy level, it is not possible to change their sanitary habits and practice higher levels of hygiene. Also, they live in highly crowded and congested areas. Thus their risk of getting infected and spreading the infection is much higher than those living in high rises. Additionally, their lack of social awareness and unstable economic conditions prevents them from practicing social distancing.

Spreading of rumours and fake news through social media has become a menace and is a pandemic in itself. In this modern world, people are insensitive to the needs of others. Selfish behavior leads to drift between people and their relationships. People become obsessed with themselves so much that they refuse to add to others'

needs. Since news channels sometimes exaggerate ordinary news, it can establish dark thoughts in the minds of the audience, hence terrifying them that they start believing in false rumours and start acting upon them. Often, this fear-mongering causes people to be insensitive towards others and is a cause of increasing the crime rate. During a pandemic outbreak, working at the local and community level fosters public trust and better adherence to rules and preventive measures.

Calling for kindness and compassion by emphasizing the danger to higher-risk groups is an effective marketing tactic because it acknowledges that different individuals are at different risk. Evolutionary theories suggest this may be due to the "grandmother effect," which liberated the group's younger members while the elders cared for the kids. One hypothesis indicates that kindness is advantageous because it causes people to feel superior to lower animals and increases the unity of communities. And it may be that when they're young people are generous to the elderly in the hope that as they get older, they can receive the same treatment.

Social networks can broaden the spread of harmful and helpful habits during an outbreak, and these effects can reach friends, friends of friends, and even friends' friends across the network. The virus itself spreads from person to person, and because people placed centrally in networks come into contact with more people, they are often among the first to become infected (134). It is not only the responsibility of government institutions to implement social distancing; the citizens are equally answerable and should be rational and sensible in their conduct. Self-control and patience surmount the hurdles and provide the zeal to handle difficult situations.

18.6. Power supply & network

The availability of electricity and regular water supply, in particular, are essential factors in coping with any pandemic. As many countries believe, and in some cases demand, that people take the need for social isolation seriously to minimize the spread of the virus, there has been an exponential increase in pressure on service providers to maintain their services. According to Smith, D. (2020) (120), "the key to maintain necessary utilities infrastructure' uninterrupted power supplies are 'only as reliable as the use of fuel."

Electricity companies often can speed up electricity restoration during non-health events, such as heavy storms, by bringing in more qualified employees from firms and contractors outside an emergency area. The proper power supply is a critical factor for the undistruptive functioning of a city. During a pandemic, physicians and primary workers' capacity to handle infected populations depends on access to adequate, uninterrupted, reliable energy in the clinic, medical equipment, and drugs (15).

A pandemic requires a speed of deployment for solutions. For many vulnerable communities, off-grid

decentralized renewable power can respond to this challenge. These energy solutions not only provide people with access to their current healthcare needs. They can also provide investment for these countries in the clean, sustainable energy infrastructure of the future (52).

18.7. Socioeconomic conditions

Socioeconomic status is a combination of financial, educational, occupational, and locational influences (17). Despite being somewhat related, each of these parameters reflects slightly varying individual and societal forces correlated with disease processes (110). Education provides the skills and qualifications required for getting a job and earning a salary. This salary, in turn, provides the means to pursue education and the other necessities of life (like food, clothes, and shelter). It finally results in a positive social, psychological, and healthy lifestyle.

A stable economic condition leads to functional social status and vice-versa. This cycle also impacts the health of an individual and their family. An individual (or a family), with a better socioeconomic status, has more chances of pursuing a healthy, hygienic lifestyle, and hence protect themselves from getting affected with an infection, than one without.

18.8. Environmental factors

The two significant environmental factors impacting infections are climatic conditions and pollution levels.

Climatic conditions

West Bengal has a tropical climate. Summer, monsoon, shortfall, and winter are the main seasons. The wet-dry tropical climate exists in the southern region and the wet subtropical climate in the North. The state has a wide range of precipitation per year with 64 inches (1 625 mm) of rainfall, of which 13 inches (330 mm) are reduced by average in August and less than 1 inch (25 mm) per year by December. The average annual temperature is 26.8°C (80.2°F), and the average temperature range from 19°C (66.20°F) to 30°C (86.0°F) (3). The city faces temperature variance during the summer and winter months, ranging from 28°-42° Celsius during the summers and a chilly 14°-26° Celsius during the winter months. Kolkata receives an average annual rainfall of 1605 mm. The weather is humid and sultry during the summer months but dry and pleasant during the winter.

Climate is an important environmental factor that can influence the spread of disease. Temperature and other climatic conditions can indirectly have an impact on health (124). Climate change results in changes to weather conditions and patterns of extreme weather events. The health effects of climate change (including climate change and extreme weather events) on human infectious diseases are affected by pathogens, hosts/vectors, and disease transmission. Firstly, the number of infectious diseases is

limited by climatic variables, both spatially and temporally. Changes in spatial and temporal climate variables affect pathogens, hosts, and their interactions with humans' development, survival, reproduction, and viability (144).

Climate change can weaken human immunity and disease-sensitivity, thereby influencing the transmission of disease. It could lead to the destruction of habitats and agricultural production strain, causing problems like crop failure, malnutrition, hunger, increased displacement of people, and conflict over land. These pressures may help increase the sensitivity of humans to infectious diseases. Waterborne diseases can prevail in some areas if there is still a lack of clean surface water for climate change. South Europe has enormous potential for the geographical spread of the malaria epidemic and other tropical diseases (56).

During the monsoons, the fluctuating humidity levels and the moisture present in the air provide the perfect condition for the infectious agents, like bacteria, viruses, fungi, and other pathogens, to breed. Different vector-borne diseases, like Dengue, Cholera, Typhoid, Influenza, and Hepatitis-A, take over the rains and affect thousands of inhabitants of the city (111). The extreme temperatures during the summer months also pave the way for a range of diseases like heat fever, a viral infection of the upper respiratory tract, skin allergies, and gastroenteritis, which wreak havoc in the city (1).

Some pathogens are transmitted by vectors to complete their life cycle and require intermediate hosts. Appropriate climatic and climatic conditions are essential for the survival, reproduction, distribution, and transmission of pathogenic diseases for vectors and hosts. Climate and weather changes can, therefore, affect the spread of infectious diseases by affecting pathogens, vectors, hosts, and livelihoods. (41).

Pollution

Environmental pollution is a significant problem and impacts the health of the human population. Pollution reaches its most severe proportions in the densely populated urban-industrial centres of the more developed countries—the unsustainable anthropogenic activities mixed with environmental pollution, which leads to significant problems with public health. Thus we need to consider pollution as a possible parameter in this model (67).

18.9. Morbidity

Morbidity refers to the signs of illness or disease within a population. It can also refer to medical problems arising from medical treatment. Morbidity is also about the risk factors associated with diseases, comparing and contrasting health events between different populations. Today, it poses a significant problem for all health conditions that can impact the population's general wellbeing (57). People with pre-morbid conditions or any

genetic endowment concerning diseases like hypertension pressure, diabetes mellitus, cancer, rheumatism, etc. are more vulnerable to high-risk infections. They are always a cause of worry for healthcare professionals, and also the economic burden of disease increases manifold for them.

18.10. Assimilation of data

The data thus collected from varied sources, for example, primary health care centre, district collector's office, municipal corporation office, local police station, Hospitals, clinics, etc. must be systematically organised in a national portal/ state portal for dissemination of accurate, reliable and timely information. This data must be collected regularly so that policymakers and citizens are aware of the current situation (136). The ground staff responsible for data collection must receive adequate training and be sensitive while dealing with private information. Confidentiality related to data sharing should remain at the highest levels.

Conclusion

Observing human reaction is instrumental in the development of a decision model for disease forecasting. Risk assessment and human reaction to the new stimuli form the basis for disruption in healthcare systems. Pandemics can overwhelm healthcare systems around the world. Humans are known to influence and adapt to changing environmental conditions. The critical factor in overcoming the pandemic is understanding how people behave in response to real and perceived risks that they face during the situation. The World Health Organization, too, recognizes the importance of human behaviour during a pandemic. According to WHO's "Outbreak Communications Planning Guide," responsible behaviour can reduce the spread of a virus as much as 80%.

The public health care system, integrated with community engagement at the block level, is known to give fruitful results. It may not be to everyone's preference to interrupt one's daily routine for others' sake. Still, throughout history humans have been willing to make sacrifices to protect others' safety. The readiness to do so appears to be a part of human nature. There is evidence from the prehistory of human communities helping aged people and people with disabilities who were unable to live on their own.

Also, a fine-tuning between central, state and local governments are required to disseminate information through trusted channels. The various forecasting models hold good, only if the warning signs are noted, and precautionary measures are taken. Public health care systems in smart cities require multilateral cooperation, communication and coordination between primary healthcare centres, digital facilities, awareness campaigns through various media channels, and setting up of 24*7 counselling centres, staff training facilities, and emergency kiosks at hospitals. The practical application

of stakeholders -behaviour based model points to the need for data management and analysis, through advanced and sophisticated techniques. These models have exploratory, predictive, and prescriptive capacities and guides on how a well organised and thoughtful data-driven modelling system can put both policymakers and modellers in an optimal position.

References

- [1] Agrawal, A. S., Sarkar, M., Chakrabarti, S., Rajendran, K., Kaur, H., Mishra, A. C., & Chawla-Sarkar, M. (2009). Comparative evaluation of real-time PCR and conventional RT-PCR during a 2 year surveillance for influenza and respiratory syncytial virus among children with acute respiratory infections in Kolkata, India, reveals a distinct seasonality of infection. *Journal of medical microbiology*, 58(12), 1616-1622.
- [2] Anderson, R. M., & May, R. M. (1992). *Infectious diseases of humans: dynamics and control*. Oxford university press.
- [3] Attri, S. D., & Tyagi, A. (2010). Climate profile of India. Environment Monitoring and Research Center, India Meteorology Department: New Delhi, India.
- [4] Azman, A. S., Luquero, F. J., Rodrigues, A., Palma, P. P., Grais, R. F., Banga, C. N., ... & Lessler, J. (2012). Urban cholera transmission hotspots and their implications for reactive vaccination: evidence from Bissau city, Guinea bissau. *PLoS neglected tropical diseases*, 6(11).
- [5] Bardak, B., & Tan, M. (2015, November). Prediction of influenza outbreaks by integrating Wikipedia article access logs and Google flu trend data. In 2015 IEEE 15th International Conference on Bioinformatics and Bioengineering (BIBE) (pp. 1-6). IEEE.
- [6] Becerra, M. C., Bayona, J., Freeman, J., Farmer, P. E., & Kim, J. Y. (2000). Redefining MDR-TB transmission 'hot spots' [Counterpoint]. *The International Journal of Tuberculosis and Lung Disease*, 4(5), 387-394
- [7] Bejon, P., Williams, T. N., Liljander, A., Noor, A. M., Wambua, J., Ogada, E., ... & Marsh, K. (2010). Stable and unstable malaria hotspots in longitudinal cohort studies in Kenya. *PLoS medicine*, 7(7).
- [8] Bell, B. P. (2016). Overview, control strategies, and lessons learned in the CDC response to the 2014–2016 Ebola epidemic. *MMWR supplements*, 65.
- [9] Bhattacharyya, D (2020). The Indian City and its 'Restive Publics'. *Modern Asian Studies*, 1-31.
- [10] Bolyard, E. A., Tablan, O. C., Williams, W. W., Pearson, M. L., Shapiro, C. N., Deitchman, S. D., & Hospital Infection Control Practices Advisory Committee. (1998). Guideline for infection control in healthcare personnel, 1998. *Infection Control & Hospital Epidemiology*, 19(6), 407-463.
- [11] Bose, R., & Ghosh, S. (2015). Slums in Kolkata: a socio-economic analysis. *The Empirical Econometrics and Quantitative Economics Letters*, 4(4), 134-148.
- [12] Bose, S. (2008). Adaptive and integrated management of wastewater and storm water drainage in Kolkata—case study of a Mega City. In *Adaptive and Integrated Water Management* (pp. 341-355). Springer, Berlin, Heidelberg.
- [13] Brankston, G., Gitterman, L., Hirji, Z., Lemieux, C., & Gardam, M. (2007). Transmission of influenza A in human beings. *The Lancet infectious diseases*, 7(4), 257-265.
- [14] Brooks, L. C., Farrow, D. C., Hyun, S., Tibshirani, R. J., & Rosenfeld, R. (2015). Flexible modeling of epidemics with an empirical Bayes framework. *PLoS computational biology*, 11(8).
- [15] Broto, V. C., & Kirshner, J. (2020). Energy access is needed to maintain health during pandemics. *Nature Energy*, 1-3.
- [16] Broussard, I. M., & Kahwaji, C. I. (2019). Universal Precautions. In *StatPearls* [Internet]. StatPearls Publishing.
- [17] Brunner, E., & Marmot, M. (2006). Social organization, stress, and health. *Social determinants of health*, 2, 17-43.
- [18] Burke, R. M. (2020). Active monitoring of persons exposed to patients with confirmed COVID-19—United States, January–February 2020. *MMWR. Morbidity and mortality weekly report*, 69.
- [19] Cahn, A., & Kumar, B. P. (2011). e role of water in India's smart cities. *Industry Water World*, 11(4).
- [20] Capasso, V., & Serio, G. (1978). A generalization of the Kermack-McKendrick deterministic epidemic model. *Mathematical Biosciences*, 42(1-2), 43-61.
- [21] Carmen, P. (1998). Epidemiology and successful control of a large outbreak due to Klebsiella pneumoniae producing extended spectrum β -lactamases. *Antimicrob Agents Chemother*, 42(1), 53-58.
- [22] Cassettari, V. C., Silveira, I. R., Balsamo, A. C., & Franco, F. (2006). Outbreak of extended-spectrum beta-lactamase-producing Klebsiella pneumoniae in an intermediate-risk neonatal unit linked to onychomycosis in a healthcare worker. *J Pediatr (Rio J)*, 82(4), 313-6.
- [23] Census of India (2011) Final population totals, West Bengal
- [24] Census of India(2011). Primary census abstract data tables, 2011. New Delhi: Government of India. Retrieved from http://www.censusindia.gov.in/2011census/PCA/PCA_Highlights/pca_highlights_india.html
- [25] Census of India. (2011). Percentage of Households to Total Households by Amenities and Assets.
- [26] Chan, J. F. W., Yuan, S., Kok, K. H., To, K. K. W., Chu, H., Yang, J., ... & Tsoi, H. W. (2020). A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *The Lancet*, 395(10223), 514-523.
- [27] Chase, V. (1996). ProMED: a global early warning system for disease. *Environmental health perspectives*, 104(7), 699-699.
- [28] Chen, F., Griffith, A., Cottrell, A., & Wong, Y. L. (2013). Behavioral responses to epidemics in an online experiment: using virtual diseases to study human behavior. *PLoS one*, 8(1).
- [29] Chretien, J. P., George, D., Shaman, J., Chitale, R. A., & McKenzie, F. E. (2014). Influenza forecasting in human populations: a scoping review. *PLoS one*, 9(4).
- [30] Cleaveland, S., Laurensen, M. K., & Taylor, L. H. (2001). Diseases of humans and their domestic mammals: pathogen characteristics, host range and the risk of emergence. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 356(1411), 991-999.
- [31] Colizza, V., Barrat, A., Barthélemy, M., Valleron, A. J., & Vespignani, A. (2007). Modeling the worldwide spread of pandemic influenza: baseline case and containment interventions. *PLoS medicine*, 4(1).
- [32] COVID, C. (19). Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), 2020.
- [33] Cox, C. S. (1998). The microbiology of air. In *Topley & Wilson's microbiology and microbial infections* (eds L.

- Collier, A. Balows & M. Sussman), pp. 339–350, 9th edn. London, UK: Arnold, Oxford University Press.
- [34] Cwiklinski, K., O'neill, S. M., Donnelly, S., & Dalton, J. P. (2016). A prospective view of animal and human Fasciolosis. *Parasite immunology*, 38(9), 558-568.
- [35] Del Valle, S. Y., Mniszewski, S. M., & Hyman, J. M. (2013). Modeling the impact of behavior changes on the spread of pandemic influenza. In modeling the interplay between human behavior and the spread of infectious diseases (pp. 59-77). Springer, New York, NY.
- [36] Desa, U. N. (2014). World urbanization prospects, the 2011 revision. Population Division, Department of Economic and Social Affairs, United Nations Secretariat.
- [37] Dukic, V., Lopes, H. F., & Polson, N. G. (2012). Tracking epidemics with Google flu trends data and a state-space SEIR model. *Journal of the American Statistical Association*, 107(500), 1410-1426.
- [38] Eames, K. T. D. (2007). Contact tracing strategies in heterogeneous populations. *Epidemiology & Infection*, 135(3), 443-454.
- [39] Eames, K. T., & Keeling, M. J. (2002). Modeling dynamic and network heterogeneities in the spread of sexually transmitted diseases. *Proceedings of the national academy of sciences*, 99(20), 13330-13335.
- [40] Eames, K. T., & Keeling, M. J. (2003). Contact tracing and disease control. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 270(1533), 2565-2571.
- [41] Epstein, P. R. (2001) Climate change and emerging infectious diseases. *Microbes and infection*, 3(9), 747-754
- [42] Ferguson, N. M., Donnelly, C. A., & Anderson, R. M. (2001). The foot-and-mouth epidemic in Great Britain: pattern of spread and impact of interventions. *Science*, 292(5519), 1155-1160.
- [43] Fornace, K. M., Drakeley, C. J., William, T., Espino, F., & Cox, J. (2014). Mapping infectious disease landscapes: unmanned aerial vehicles and epidemiology. *Trends in parasitology*, 30(11), 514-519.
- [44] Funk, S., Salathé, M., & Jansen, V. A. (2010). Modelling the influence of human behaviour on the spread of infectious diseases: a review. *Journal of the Royal Society Interface*, 7(50), 1247-1256.
- [45] Ganguly, K. S., Modak, S., Chattopadhyay, A. K., Ganguly, K. S., Mukherjee, T. K., Dutta, A., & Biswas, D. (2016). Forecasting Based On a SARIMA Model of Urban Malaria for Kolkata. *American Journal of Epidemiology and Infectious Disease*, 4, 22-33.
- [46] Ganguly, K. S., Modak, S., Ganguly, K. S., & Chattopadhyay, A. K. (2016). Study on Temporal Effects of Urban Malaria Incidences. *International Journal*, 5(2), 121.
- [47] Garner, M. G., & Hamilton, S. A. (2011). Principles of epidemiological modelling. *Revue Scientifique et Technique-OIE*, 30(2), 407.
- [48] Garrick, D. E., Hall, J. W., Dobson, A., Damania, R., Grafton, R. Q., Hope, R., ... & O'Donnell, E. (2017). Valuing water for sustainable development. *Science*, 358(6366), 1003-1005.
- [49] Germann, T. C., Kadau, K., Longini Jr, I. M., & Macken, C. A. (2006). From the cover: mitigation strategies for pandemic influenza in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, 103(15), 5935.
- [50] Grefenstette, J. J., Brown, S. T., Rosenfeld, R., DePasse, J., Stone, N. T., Cooley, P. C., & Guclu, H. (2013). FRED (A Framework for Reconstructing Epidemic Dynamics): an open-source software system for modeling infectious diseases and control strategies using census-based populations. *BMC public health*, 13(1), 940.
- [51] Gross, T., D'Lima, C. J. D., & Blasius, B. (2006). Epidemic dynamics on an adaptive network. *Physical review letters*, 96(20), 208701.
- [52] Hagan, P., Maguire, B., & Bopping, D. (2008). Public behaviour during a pandemic. *Australian Journal of Emergency Management*, the, 23(3), 35.
- [53] Halloran, M. E., Longini, I. M., Nizam, A., & Yang, Y. (2002). Containing bioterrorist smallpox. *Science*, 298(5597), 1428-1432.
- [54] Haque, I., Mehta, S., & Kumar, A. (2019). Towards Sustainable and Inclusive Cities: The Case of Kolkata.
- [55] Harvey, N., Reeves, A., Schoenbaum, M. A., Zagmutt-Vergara, F. J., Dubé, C., Hill, A. E., Corso, B.A., McNab, W.B., Cartwright, C.I. & Salman, M. D. (2007). The North American Animal Disease Spread Model: A simulation model to assist decision making in evaluating animal disease incursions. *Preventive veterinary medicine*, 82(3-4), 176-197.
- [56] Hay, S. I., Cox, J., Rogers, D. J., Randolph, S. E., Stern, D. I., Shanks, G. D., ... & Snow, R. W. (2002). Climate change and the resurgence of malaria in the East African highlands. *Nature*, 415(6874), 905-909.
- [57] Hernandez, J. B. R., & Kim, P. Y. (2019). *Epidemiology Morbidity and Mortality*.
- [58] Hirschtick, R. E., Glassroth, J., Jordan, M. C., Wilcosky, T. C., Wallace, J. M., Kvale, P. A., ... & Pulmonary Complications of HIV Infection Study Group. (1995). Bacterial pneumonia in persons infected with the human immunodeficiency virus. *New England Journal of Medicine*, 333(13), 845-851.
- [59] Hotez, P. J. (2014). Ten global “hotspots” for the neglected tropical diseases. *PLoS Neglected Tropical Diseases*, 8(5).
- [60] Huerta, R., & Tsimring, L. S. (2002). Contact tracing and epidemics control in social networks. *Physical Review E*, 66(5), 056115.
- [61] Hyman, J. M., Li, J., & Stanley, E. A. (2003). Modeling the impact of random screening and contact tracing in reducing the spread of HIV. *Mathematical biosciences*, 181(1), 17-54.
- [62] Jones, K. E., Patel, N. G., Levy, M. A., Storeygard, A., Balk, D., Gittleman, J. L., & Daszak, P. (2008). Global trends in emerging infectious diseases. *Nature*, 451(7181), 990-993.
- [63] Joyce, J. (2003). Bayes' theorem.
- [64] Kahn, J. S., & McIntosh, K. (2005). History and recent advances in coronavirus discovery. *The Pediatric infectious disease journal*, 24(11), S223-S227.
- [65] Kapuria, P. (2018). Valuing Water for a Smart and Sustainable City: Lessons from Kolkata.
- [66] Keeling, M. J., Woolhouse, M. E., Shaw, D. J., Matthews, L., Chase-Topping, M., Haydon, D. T., & Grenfell, B. T. (2001). Dynamics of the 2001 UK foot and mouth epidemic: stochastic dispersal in a heterogeneous landscape. *Science*, 294(5543), 813-817.
- [67] Khan, M. A., & Ghouri, A. M. (2011). Environmental pollution: Its effects on life and its remedies. *Researcher World: Journal of Arts, Science & Commerce*, 2(2), 276-285.)
- [68] Khatoon, S., & Khan, M. M. A. (2020). Socio-Economic Status and Burden of Malaria in Kolkata Municipal Corporation (KMC) Area, West Bengal. *Journal of Communicable Diseases (E-ISSN: 2581-351X & P-ISSN: 0019-5138)*, 52(1), 72-77.

- [69] Kiss, I. Z., Green, D. M., & Kao, R. R. (2006). Infectious disease control using contact tracing in random and scale-free networks. *Journal of the Royal Society Interface*, 3(6), 55-62.
- [70] KMA (2018). https://www.kmdaonline.org/home/about_us
- [71] KMC (2018). <https://www.kmcgov.in/KMCPortal/jsp/KMCPortalHome1.jsp>
- [72] KMC (2020). <https://www.kmcgov.in/KMCPortal/jsp/KMCHHealthDiseaseControl.jsp>
- [73] Koher, A., Lentz, H. H., Gleeson, J. P., & Hövel, P. (2019). Contact-based model for epidemic spreading on temporal networks. *Physical Review X*, 9(3), 031017.
- [74] Lessler, J., Azman, A. S., McKay, H. S., & Moore, S. M. (2017). What is a hotspot anyway? *The American journal of tropical medicine and hygiene*, 96(6), 1270-1273.
- [75] Lloyd, A. L. (2001). Realistic distributions of infectious periods in epidemic models: changing patterns of persistence and dynamics. *Theoretical population biology*, 60(1), 59-71.
- [76] Macfarlane, J. (2002). Severe pneumonia and a second antibiotic. *The Lancet*, 359(9313), 1170-1172.
- [77] Maldin, B., & Criss, K. (2006). Risky business: planning for pandemic flu. *Biosecurity and bioterrorism: biodefense strategy, practice, and science*, 4(3), 307-312.
- [78] Mansfield, T. A. (2012). Calcutta, from fort to city: a study of a colonial settlement, 1690-1750 (Doctoral dissertation, University of Leicester).
- [79] McPhearson, T., Parnell, S., Simon, D., Gaffney, O., Elmqvist, T., Bai, X., & Revi, A. (2016). Scientists must have a say in the future of cities. *Nature*, 538(7624), 165-166.
- [80] Meyers, L. A., Pourbohloul, B., Newman, M. E., Skowronski, D. M., & Brunham, R. C. (2005). Network theory and SARS: predicting outbreak diversity. *Journal of theoretical biology*, 232(1), 71-81.
- [81] Miller, J. C. (2007). Predicting the size and probability of epidemics in a population with heterogeneous infectiousness and susceptibility. *arXiv preprint q-bio/0702007*.
- [82] Miller, J. C. (2009). Spread of infectious disease through clustered populations. *Journal of the Royal Society Interface*, 6(41), 1121-1134.
- [83] Mookherjee, S. (2002). Problem of waterlogging of Calcutta. *Changing Environmental Scenario of the Indian Subcontinent*. ACB Publications, Kolkata, 455-460.
- [84] Moreno, E. L., & Warah, R. (2006). The State of the World's Cities Report 2006/7: Urban and slum trends in the 21st century. *Un Chronicle*, 43(2), 24.
- [85] Morens, D. M., Folkers, G. K., & Fauci, A. S. (2004). The challenge of emerging and re-emerging infectious diseases. *Nature*, 430(6996), 242-249.
- [86] Morse, S. S. (1995). Factors in the Emergence of Infectious Diseases. *CDC. Emerging Infectious Diseases Journal*, 1(1).
- [87] Mukherjee, M. (2012). Urban growth and spatial transformation of Kolkata metropolis: a continuation of colonial legacy. *ARNP Journal of Science and Technology*, 2, 365-380.
- [88] Mukherjee, S., Bebermeier, W., & Schütt, B. (2018). An Overview of the Impacts of Land Use Land Cover Changes (1980–2014) on Urban Water Security of Kolkata. *Land*, 7(3), 91.
- [89] Müller, J., Kretzschmar, M., & Dietz, K. (2000). Contact tracing in stochastic and deterministic epidemic models. *Mathematical biosciences*, 164(1), 39-64
- [90] Munz, P., Hudea, I., Imad, J., & Smith, R. J. (2009). When zombies attack!: mathematical modelling of an outbreak of zombie infection. *Infectious Disease Modelling Research Progress*, 4, 133-150.
- [91] Musa, S. (2018). Smart cities-a road map for development. *IEEE Potentials*, 37(2), 19-23.
- [92] Myers, M. F., Rogers, D. J., Cox, J., Flahault, A., & Hay, S. I. (2000). Forecasting disease risk for increased epidemic preparedness in public health. *Advances in parasitology*, 47, 309.
- [93] Nair, P. T. (1986). *Calcutta in the 17th century* (Vol. 1). Firma KLM.
- [94] Nath, K. J., & Majumdar, A. (1990). Drainage, sewerage and waste disposal. *Sukanta Chaudhuri* (Hg.). Calcutta. *The Living City*, 2, 167-72.
- [95] Ndiaye, B. M., Tendeng, L., & Seck, D. (2020). Analysis of the COVID-19 pandemic by SIR model and machine learning techniques for forecasting. *arXiv preprint arXiv:2004.01574*.
- [96] Nsoesie, E. O., Brownstein, J. S., Ramakrishnan, N., & Marathe, M. V. (2014). A systematic review of studies on forecasting the dynamics of influenza outbreaks. *Influenza and other respiratory viruses*, 8(3), 309-316.
- [97] Osterholm, M. T., Kelley, N. S., Sommer, A., & Belongia, E. A. (2012). Efficacy and effectiveness of influenza vaccines: a systematic review and meta-analysis. *The Lancet infectious diseases*, 12(1), 36-44.
- [98] Osterholm, M. T., Moore, K. A., Kelley, N. S., Brosseau, L. M., Wong, G., Murphy, F. A., ... & Kapetshi, J. (2015). Transmission of Ebola viruses: what we know and what we do not know. *MBio*, 6(2).
- [99] Osthus, D., Gattiker, J., Priedhorsky, R., & Del Valle, S. Y. (2019). Dynamic Bayesian influenza forecasting in the United States with hierarchical discrepancy (with discussion). *Bayesian Analysis*, 14(1), 261-312.
- [100] Osthus, D., Hickmann, K. S., Caragea, P. C., Higdon, D., & Del Valle, S. Y. (2017). Forecasting seasonal influenza with a state-space SIR model. *The annals of applied statistics*, 11(1), 202
- [101] Palit, A., Batabyal, P., Kanungo, S., & Sur, D. (2012). In-house contamination of potable water in the urban slum of Kolkata, India: a possible transmission route of diarrhea. *Water Science and Technology*, 66(2), 299-303.
- [102] Pavlovsky, E. N. (1966). Natural Nidality of Transmissible Diseases with special reference to the Landscape Epidemiology of Zoonoses. *Natural Nidality of Transmissible Diseases with special reference to the Landscape Epidemiology of Zoonoses*.
- [103] Peter, W., & Horby, D. P. (2013). Prospects for emerging infections in East and Southeast Asia 10 years after severe acute respiratory syndrome. *Emerging infectious diseases*, 19(6), 853.
- [104] Phillips, B. L., & Puschendorf, R. (2013). Do pathogens become more virulent as they spread? Evidence from the amphibian declines in Central America. *Proceedings of the Royal Society B: Biological Sciences*, 280(1766), 20131290.
- [105] Pratt, D. J., & Gwynne, M. D. (1977). *Rangeland management and ecology in East Africa*. Hodder and Stoughton.
- [106] Quereda, C., Corral, I., Laguna, F., Valencia, M. E., Tenorio, A., Echeverria, J. E., ... & Gonzalez-Lahoz, J. M. (2000). Diagnostic utility of a multiplex herpesvirus PCR

- assay performed with cerebrospinal fluid from human immunodeficiency virus-infected patients with neurological disorders. *Journal of clinical microbiology*, 38(8), 3061-3067.
- [107] Randolph, S. E., & Rogers, D. J. (1997). A generic population model for the African tick *Rhipicephalus appendiculatus*. *Parasitology*, 115(3), 265-279.
- [108] Read, J. M., & Keeling, M. J. (2003). Disease evolution on networks: the role of contact structure. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 270(1516), 699-708.
- [109] Rodriguez-Rajo, F. J., Méndez, J., & Jato, V. (2005). Airborne Ericaceae pollen grains in the atmosphere of Vigo (Northwest Spain) and its relationship with meteorological factors. *Journal of Integrative Plant Biology*, 47(7), 792-800.
- [110] Root, E. D., Rodd, J., Yunus, M., & Emch, M. (2013). The role of socioeconomic status in longitudinal trends of cholera in Matlab, Bangladesh, 1993–2007. *PLoS neglected tropical diseases*, 7(1).
- [111] Saha, D. R., Rajendran, K., Ramamurthy, T., Nandy, R. K., & Bhattacharya, S. K. (2008). Intestinal parasitism and *Vibrio cholerae* infection among diarrhoeal patients in Kolkata, India. *Epidemiology & Infection*, 136(5), 661-664.
- [112] Sau, A. (2017). A study on water supply and sanitation at a slum in Kolkata. *Int. J. Med. Sci. Public Health*, 6, 634-638.
- [113] Schwandt, T. A., Denzin, N. K., & Lincoln, Y. S. (1994). *Handbook of qualitative research*. Londres, Ed: Denzin & Lincoln.
- [114] Seto, W. H. (2015). Airborne transmission and precautions: facts and myths. *Journal of Hospital Infection*, 89(4), 225-228.
- [115] Shabbir, G., Khan, H., & Sadiq, M. A. (2010). A note on Exact solution of SIR and SIS epidemic models. *arXiv preprint arXiv:1012.5035*.
- [116] Shah, P. B., Giudice, J. C., Griesback, R., Morley, T. F., & Vasoya, A. (2004). The newer guidelines for the management of community-acquired pneumonia. *The Journal of the American Osteopathic Association*, 104(12), 521-526.
- [117] Shao, Y., & Wu, J. (2020). IDM editorial statement on the 2019-nCoV. *Infectious Disease Modelling*, 5, 233.
- [118] Siegel, J. D., Rhinehart, E., Jackson, M., Chiarello, L., & Health Care Infection Control Practices Advisory Committee. (2007). 2007 guideline for isolation precautions: preventing transmission of infectious agents in health care settings. *American journal of infection control*, 35(10), S65.
- [119] Sikarwar, A., & Chattopadhyay, A. (2020). Population Dynamics in Top Seven Cities of India. In *Analyzing Population and Land Use Change* (pp. 21-30). Springer, Singapore.
- [120] Smith, D. C. (2020). COVID-19 and the energy and natural resources sectors: little room for error.
- [121] Soebiyanto, R. P., Adimi, F., & Kiang, R. K. (2010). Modeling and predicting seasonal influenza transmission in warm regions using climatological parameters. *PLoS one*, 5(3).
- [122] Srivastava, A., Nagpal, B. N., Joshi, P. L., Paliwal, J. C., & Dash, A. P. (2009). Identification of malaria hot spots for focused intervention in tribal states of India: a GIS based approach. *International Journal of Health Geographics*, 8(1), 30.
- [123] Streitz, N. (2019). Beyond ‘smart-only cities: redefining the ‘smart-everything paradigm. *Journal of Ambient Intelligence and Humanized Computing*, 10(2), 791-812.
- [124] Sumi, A., Rajendran, K., Ramamurthy, T., Krishnan, T., Nair, G. B., Harigane, K., & Kobayashi, N. (2013). Effect of temperature, relative humidity and rainfall on rotavirus infections in Kolkata, India. *Epidemiology & Infection*, 141(8), 1652-1661.
- [125] Sur, D., Manna, B., Deb, A. K., Deen, J. L., Danovaro-Holliday, M. C., von Seidlein, L., ... & Bhattacharya, S. K. (2004). Factors associated with reported diarrhoea episodes and treatment-seeking in an urban slum of Kolkata, India. *Journal of Health, Population and Nutrition*, 130-138.
- [126] Tang, J. W. (2009). The effect of environmental parameters on the survival of airborne infectious agents. *Journal of the Royal Society Interface*, 6(suppl_6), S737-S746.
- [127] Tellier, R. (2006). Review of aerosol transmission of influenza A virus. *Emerging infectious diseases*, 12(11), 1657.
- [128] Tellier, R. (2009). Aerosol transmission of influenza A virus: a review of new studies. *Journal of the Royal Society Interface*, 6(suppl_6), S783-S790.
- [129] Thompson, R. N., & Brooks-Pollock, E. (2019). Detection, forecasting and control of infectious disease epidemics: modelling outbreaks in humans, animals and plants.
- [130] Thomsen, R. W., Hundborg, H. H., Lervang, H. H., Johnsen, S. P., Schønheyder, H. C., & Sørensen, H. T. (2004). Risk of community-acquired pneumococcal bacteremia in patients with diabetes: a population-based case-control study. *Diabetes Care*, 27(5), 1143-1147.
- [131] Thrall, P. H., & Burdon, J. J. (2003). Evolution of virulence in a plant host-pathogen metapopulation. *Science*, 299(5613), 1735-1737.
- [132] Towers, S., & Feng, Z. (2009). Pandemic H1N1 influenza: predicting the course of a pandemic and assessing the efficacy of the planned vaccination programme in the United States. *Eurosurveillance*, 14(41), 19358.
- [133] Van Baalen, M., & Rand, D. A. (1998). The unit of selection in viscous populations and the evolution of altruism. *Journal of theoretical biology*, 193(4), 631-648.
- [134] Van Bavel, J. J., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., ... & Drury, J. (2020). Using social and behavioural science to support COVID-19 pandemic response. *Nature Human Behaviour*, 1-12.
- [135] Varia, M., Wilson, S., Sarwal, S., McGeer, A., Gournis, E., & Galanis, E. (2003). Investigation of a nosocomial outbreak of severe acute respiratory syndrome (SARS) in Toronto, Canada. *Cmaj*, 169(4), 285-292.
- [136] Viboud, C., Boëlle, P. Y., Carrat, F., Valleron, A. J., & Flahault, A. (2003). Prediction of the spread of influenza epidemics by the method of analogues. *American Journal of Epidemiology*, 158(10), 996-1006.
- [137] Wang, L., Chen, J., & Marathe, M. (2020). TDEFSI: Theory-guided Deep Learning-based Epidemic Forecasting with Synthetic Information. *ACM Transactions on Spatial Algorithms and Systems (TSAS)*, 6(3), 1-39.
- [138] Weiss, H. H. (2013). The SIR model and the foundations of public health. *Materials mathematics*, 0001-17.
- [139] Wolf, M., & Weissing, F. J. (2010). An explanatory framework for adaptive personality differences. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1560), 3959-3968.
- [140] Woolhouse, M. E., & Gowtage-Sequeria, S. (2005). Host range and emerging and reemerging pathogens. *Emerging infectious diseases*, 11(12), 1842.

- [141] World Health Organization. (2004). Practical guidelines for infection control in health care facilities.
- [142] World Health Organization. (2005). Practical guidelines for infection control in health care facilities (No. Regional Publication No. 41). WHO Regional Office for South-East Asia.
- [143] World Health Organization. (2005). Using climate to predict infectious disease epidemics.
- [144] World Health Organization. (2020). Modes of transmission of virus causing COVID-19: implications for IPC precaution recommendations: scientific brief, 27 March 2020 (No. WHO/2019-nCoV/Sci_Brief/Transmission_modes/2020.1). World Health Organization.
- [145] Zawacki, A., O'Rourke, E., Potter-Bynoe, G., Maccone, A., Harbarth, S., & Goldmann, D. (2004). An outbreak of *Pseudomonas aeruginosa* pneumonia and bloodstream infection associated with intermittent otitis externa in a healthcare worker. *Infection Control & Hospital Epidemiology*, 25(12), 1083-1089.
- [146] Zhou, J., Wei, J., Choy, K. T., Sia, S. F., Rowlands, D. K., Yu, D., Wu, C.Y., Lindsley, W.G., Cowling, B.J., McDevitt, J. & Peiris, M. (2018). Defining the sizes of airborne particles that mediate influenza transmission in ferrets. *Proceedings of the National Academy of Sciences*, 115(10), E2386-E2392.