



Review of Geospatial Technology for Infectious Disease Surveillance: Use Case on COVID-19

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Abstract

This paper discusses on the increasing relevancy of geospatial technologies such as geographic information system (GIS) in the public health domain, particularly for the infectious disease surveillance and modelling strategies. Traditionally, the disease mapping tasks have faced many challenges—(1) authors rarely documented the evidence that were used to create map, (2) before evolution of GIS, many errors aroused in mapping tasks which were expanded extremely at global scales, and (3) there were no fidelity assessment of maps which resulted in inaccurate precision. This study on infectious diseases geo-surveillance is divided into four broad sections with emphasis on handling geographical and temporal issues to help in public health decision-making and planning policies: (1) geospatial mapping of diseases using its spatial and temporal information to understand their behaviour across geography; (2) the citizen's involvement as volunteers in giving health and disease data to assess the critical situation for disease's spread and prevention in neighbourhood effect; (3) scientific analysis of health-related behaviour using mathematical epidemiological and geo-statistical approaches with (4) capacity building program. To illustrate each theme, recent case studies are cited and case studies are performed on COVID-19 to demonstrate selected models.

Keywords Geospatial technology · Citizen Science · Public health · COVID-19 · Mathematical epidemiology

Introduction

The public health sector's increasing demand for mapping, analytics and visualization had started a date back in the last 20 years, which has resulted in a growing information-age technology for communicable disease surveillance and epidemiology (Baker et al. 1995; Bos and Blobel 2007; Friede et al. 1993; Friede 1995; Khan et al. 2010; Reeder et al. 2012; Yu and Edberg 2005). This continuous public health burden with advances in information technology

combined with spatial data led to the development of various tools and systems that provides visualization of disease data in space and time (Dredger et al. 2007; Kothari et al. 2008; Robertson and Nelson 2010; Schriml et al. 2009).

The first integral definition of public health was given by Winslow (1920) as “science and art of preventing disease, prolonging life, and promoting health through the organized efforts and informed choices of society, organizations, public and private communities, and individuals”. The American Public Health Association (APHA) mentioned public health as a practice of preventing the spread of disease and an aim of promoting good health from small communities to across the world (Turnock 2012). Advances in information technology and spatial features resulted in geospatial technology which is acute for mapping, surveillance, predicting outbreaks, detecting clustering and analysing spread patterns of infectious diseases with epidemic or pandemic potential in communities and across territories (AvRuskin et al. 2004; Carpenter 2011; Castronovo et al. 2009; Dominkovics et al. 2011; Gao et al.

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2008; Heymann and Brilliant 2011; Hills et al. 2008; Klompas et al. 2011; Reis et al. 2007). Geospatial technology has provided visualization and analytical tools to public health professionals and decision makers to execute diseases control programs in affected and/or suspected regions and make analysis and predictions possible that was once technologically out of reach.

Geospatial technology includes geographical information systems (GIS), global positioning systems (GPS) and satellite-based technologies such as remote sensing (RS). GIS is known for geographic data capture, input, update, manipulation, transformation, analysis, query, modelling and visualization of all forms of geographically referenced information through the set of computer programs (Bonham-Carter 2014). GPS provides positioning, navigation and timing (PNT) services by capturing data from satellites and providing it to users (Eldredge et al. 2010), and RS is an earth observation instrument that delivers regional information on climatic factors and landscape features. Therefore, GPS and RS provide regional and spatial information, while GIS provides geospatial data integration as well as accurate geospatial analysis in real-time manner (Zhen et al. 2010).

Geospatial Technology and Infectious Disease Surveillance

Infectious diseases mostly adapts anti-microbial and mobility features later formed in a shape of pandemic and/or epidemic (Chen et al. 2019; Cheng et al. 2019; Lee and Nishiura 2019), which forced public health authorities to understand not only the diseases virulence, but also its demographic and environmental factors that helps in making spread patterns though space and time domain (Croner 2004). For example, the global spread of highly pathogenic avian influenza (HPAI) H5N1 in 2005–06 with no effective vaccines led to concern among public health decision makers, in spite of many international programs (Rappole and Hubálek 2006)³². The reason behind their concern was they were lacking of disease surveillance tool in its initial stage which caused inaccessibility to populations at risk, and faced difficulties in implementing immunization strategies at a global scale (Kitler et al. 2002; Stoto et al. 2004). However, the impact of environmental and demographic factors also plays a major role as this can inform about the interaction between hosts and pathogens, and patterns of spread in space and time.

The GIS provides dynamic maps to understand geographical distribution of diseases for analysis on frequency of cases, disease mapping, spatial cluster of diseases, disease association with environmental factors, network analysis, etc. With such a visualization and analytical

capabilities, GIS technology is holding a widespread growth in public health (Ahmad et al. 2011a, b; Booman et al. 2000; Hanafi-Bojd et al. 2012; Kolivras 2006; Martin et al. 2002; Nykiforuk and Flaman 2011; Abdul Rasam et al. 2011; Zhang et al. 2008; Zhen et al. 2010). The seamless integration of GIS with real-time infectious disease-related diverse datasets through web-based mapping leads to the development of geospatial dashboard, geospatial service framework, for infectious disease surveillance (Dent 2006; Gao et al. 2008; Yun 2007). The infectious disease-related data might include disease surveillance data (active/confirmed cases) and health system data (hospital visits, emergency services availability, nurse/doctor availability, ICU/bed availability). Many open-source geospatial standards of Open Geospatial Consortium (OGC) are used as a Web Map Service (WMS), Web Coverage Service (WCS), Web Processing Service (WPS), Web Feature Service (WFS), etc. (Bulatović et al. 2010; Gao et al. 2008) to visualize, access, publish and manipulate geospatial resources. Also, many other popular industrial geospatial standards are developed by ESRI, Google, Yahoo, and MapInfo (Granell et al. 2014) to fetch location-based data and provide infectious disease surveillance dashboard to monitor and control the geographically spread of disease (Zhang et al. 2007). The Geocoded Really Simple Syndication (GeoRSS) tagged XML files from GeoRSS services can also be used to provide geocoded infectious disease news from social media platform (Tolentino et al. 2007; Kass-Hout and Alhinnawi 2013a, b; Kodong et al. 2020).

Historical Context

The mapping of infectious diseases using geospatial and information technology to benefit public health is not a new way of tracking the diseases (Ahmad et al. 2017; Cui et al. 2011; Hirsch 1883; Hornsby 2000; Matthew et al. 2004; May 1951; Mujica 2013; Nicholson and Mather 1996; Noble et al. 2012; Perl and Moalem 2006; Williams et al. 1986). The historical disease mapping has faced many challenges—(1) authors rarely documented the evidence that were used to create map, (2) after mapping had been implemented before the beginning of geographical information systems, many errors arouse which were expanded extremely at global scales, and (3) there were no fidelity assessment of maps which resulted in inaccurate precision. But nowadays, wide range of geospatial applications are available in public health community with a possibilities of visualization, analysis, detection of clusters formed and calculate disease-related metrics such as incidence and prevalence rate (Beck et al. 2000; Clarke et al. 1996; Hay 2000; Jacquez 2000; Kleinschmidt et al. 2000; Lawson and

Leimich 2000; Moore and Carpenter 1999; Robinson 2000; Wilkinson et al. 1998).

The earliest mapping for visualisation of the link between disease and place was done in 1694 on plague epidemic in Italy (Dent 2006). During cholera outbreak in 1854, the study of physician John Snow had made a novel contribution in history of public health and epidemiology by using cartography applications and geographic visualization in fighting cholera. After 225 years, the maps were identified as a communication tool in understanding and tracking of infectious diseases, such as the 1918 influenza pandemic, yellow fever, and cholera. Since then revolution of web-based tools started in applied health geography (Boulos 2008). The trend of infectious disease mapping could be seen from 2014 review of the Health GIS literature which demonstrated that 248 research papers out of 865 were focused on infectious disease mapping (Lyseen et al. 2014).

Covid-19

The ongoing pandemic outbreak targeting humans' respiratory system was recently discovered in December 2019 by the name of Coronavirus Disease 19 (Covid-19) (World Health Organization) from a cluster of patients with acute respiratory distress syndrome in Wuhan, Hubei Province, China (Huang et al. 2020; Lu et al. 2020a, b) and spread globally by March 2020. This pathogenic disease is structurally related to the Coronavirus (CoV), which belongs to family *Coronaviridae* and the order *Nidovirales*. This family is classified into four genera—*Alphacoronavirus*, *Betacoronavirus*, *Gammacoronavirus*, and *Deltacoronavirus*, on the basis of their phylogenetic and genomic analysis. The species of *Alphacoronavirus* and *Betacoronavirus* infect mammals, causes respiratory illness in humans and gastroenteritis in animals, while species of *Gammacoronaviruses* and *Deltacoronaviruses* infect birds, but some of them can also infect mammals (Woo et al. 2012). The two virus species from *Betacoronavirus* genus—Severe Acute Respiratory Syndrome (SARS-CoV) or Middle East Respiratory Syndrome (MERS-CoV)—had earlier demonstrated that coronaviruses can cause significant public threat (Ge et al. 2013). The COVID-19 is categorized into *Betacoronavirus* by World Health Organization (WHO) on the basis of genomic sequencing analysis of lower respiratory tract samples, which is obtained from total of nine patients (Huang et al. 2020; Lu et al. 2020a, b). COVID-19 has started behaving like the once-in-a-century pandemic by affecting healthy adults as well as elderly people with some health issues and by infecting others at an exponential rate of increase than SARS or MERS.

Geospatial Technology

During occurrence of diseases, geospatial technologies and services could help in representing the spatio-temporal information and in analysing the dynamic spread of diseases. As mentioned by Boulos (2004), geospatial technologies and services, which performs in real time manner, are tremendously relevant to create a “spatial health information infrastructure”. In this section, a review on many geospatial technologies with enabled IT services is carried out to understand and analyse the spread and outbreak of disease with a case study on COVID-19 pandemic.

Citizen Science

The expansion of Citizen Science from biodiversity and ecological domain (Haklay 2013; Miller-Rushing et al. 2012) to public health community across spatial extents made an urgent need to study its different forms (Crowl et al. 2008). The in-depth report of EU describes taxonomy of Citizen Science in three levels (European Commission 2013), described in Roy et al. (2012), Wiggins and Crowston (2011) and Haklay (2013). Roy et al. (2012) categorized Citizen Science by participant's number and of their spread (“local” and “mass”) and “thoroughness” (time and resource investment), or King et al. (2016) described “for the people, with the people, or by the people” about Citizen Science activities. Wiggins and Crownston (2011) classified Citizen Science projects in conservation (managing natural resources), action (addressing local issues and concerns), investigation (answering scientific questions), and education (providing knowledge to citizens). Haklay (2013) classified Citizen Science into four levels based on participant's engagement—(1) level 1 is crowdsourcing in which citizens with less or no knowledge on activity perform as sensors to complete computing tasks, (2) level 2 is distributed intelligence where citizens are being trained with skills for interpretation of collected data, (3) level 3 is participatory science in which citizens decide about research questions and types of data to be collected, and (4) level 4 is extreme where citizens are fully involved in defining research strategies, data collection, data interpretation, and performing scientific analysis. Apparently, the concept of Citizen Science is rare in public health domain, but some of its contribution seen in some studies which not only helps in predicting disease risks but also in combating the infectious diseases (Curtis-Robles et al. 2015; Palmer et al. 2017; Smolinski et al. 2015; Wilson et al. 2014).

Another approach similar to Citizen Science is ‘popular epidemiology’, in which experts and laypersons jointly

collect environmental data responsible for particular health consequences (Brown 2013), or ‘street science’ as a process in which general public communities actively engaged in defining problems, framing of research questions, and decision-making activities about research design (Corburn 2007).

Crowdsource/VGI Mobile Apps

Despite technological and computational developments in GeoWeb, many web technologies (such as jQuery and AJAX), mapping APIs (like Google), and GPS devices resulted in a new revolution of neogeography (Turner 2006), where mapping is done by crowd and can be reached by anyone from general public members group. Such revolution brought a trend of Volunteered Geographic Information (VGI), which is first coined and explained by Goodchild (2007a). According to Goodchild (2007b), VGI highlighted the human capabilities in collecting geospatial information by using five senses and then integrating with external sensors of mobile devices like GPS, accelerometer, camera, digital compass and microphone gives valuable datasets which can neither be retrieved from satellite imagery nor collected with any GPS receivers. Another successful term in geospatial mapping using mobile technology is crowdsourcing (Heipke 2010; Hudson-Smith et al. 2009), which was coined by Howe (2006), that involves the collection of geospatial information or mapping of any particular activity by an undefined crowd or network of people. Both terms, VGI and crowdsourcing, slightly differ but they are usually recognized as a synonyms or even as a combined term, “crowdsourcing geographic information” (Sui et al. 2013). Over the last decade, VGI-oriented open-source mobile apps are EpiCollect (Aanensen et al. 2009) for ecology and epidemiology; NoiseTube (Maisonneuve et al. 2010) (<http://noisetube.net>) and Noise Battle (Garcia-Martí et al. 2013) for noise monitoring; Skywatch Windoo (<http://windoo.ch>) for weather monitoring; Mappiness (<http://www.mappiness.org.uk>) for behavioural analysis (MacKerron and Mourato 2010).

The open-source mechanism for data collection using Android devices can be performed by Open Data Kit (ODK) suite¹⁰⁷ (<https://opendatakit.org>), which is composed of ODK Collect and ODK Aggregate. ODK Collect (<https://opendatakit.org/use/collect>) provides a customizable framework for geospatial data collection, and ODK Aggregate is a web application that runs on Apache Tomcat server (<http://tomcat.apache.org>) to store collected data through a synchronization with a database, for example, PostgreSQL (Brunette et al. 2013). As such, suite’s performance can be seen in various activities like agricultural monitoring (Krosing and Roybal 2013),

monitoring of deforestation and school attendance, documentation of war crimes, and health programs (Anokwa et al. 2009).

Digital Contact Tracing

Nowadays, COVID-19 has become the greatest threat for public health in last 100 years, and due to such pandemic, various levels of lockdown are issued across the world to break its chain of infection transmission. However, this is the first approach to invade the contagion, but once it would be lifted, this pandemic would start in a new way and might reach its highest peak by infecting more and more population (Ferguson et al. 2020). Therefore, to combat with such a global pandemic threat, another approach is discovered by a group of researchers, known as digital contact tracing.

Smartphone-based contact tracing is known as a digital contact tracing which presents a sustainable solution to limit the transmission of infectious disease by tracing their potential transmission routes in a population; however, such an app presents significant concerns regarding privacy. The digital contact tracing works on the principle of ‘crowdsource data’ by measuring the proximity to an infectious person. In previous diseases risk surveillance, the contact tracing apps were used to pool location timestamped data to determine the exposures to risk of infections (Sacks et al. 2015). Such data are highly personal and lead many privacy concerns (Smith et al. 2012), but they were not always accurate to infer the exposure risks due to noisy data (Farrahi et al. 2014). Therefore, various smartphone apps are developed in COVID-19 pandemic in which some apps use location for proximity and some of them are not using location services of mobile device subject to the privacy-preserving nature.

COVID-19 Contact Tracing

In order to illuminate the epidemiology of COVID-19 and to characterize its severity (Lipsitch et al. 2020), there is an urgent need of digital platform that captures real-time accurate information on COVID-19 patients, diseases, diagnosis, treatment, and clinical reports, and whom they get interacted at which place to detect clusters and generate alerts. Such information may help in understanding risk factors of infection and in predicting the next generation of infectious persons (FitzGerald 2020). Addressing this unprecedented challenge, many mobile apps have been developed and are being used at large scale, and some of them are as follows:

- **COVID Symptom Study (COVID Symptom Tracker)**—This mobile app is developed in collaboration of Zoe Global Ltd., a digital health care company, and a group of academic scientists from Massachusetts General Hospital and King's College London, which was launched in UK on March 24, 2020, and became available after 5 days in USA. This app enquires about age, location, and other diseases risks, and also, a self-reporting function is enabled which is associated with COVID-19 infection and exposure (Drew et al. 2020). This app retrieve updates on healthcare worker's experiences who are on COVID-19 duty, their stress and anxiety, and use of personal protective equipment (PPE) kits are being surveyed through this app to observe intensity of health care workers (Drew et al. 2020).
- **Aarogya Setu**—This mobile app is launched on April 2, 2020, by Government of India to aware general public on COVID-19 symptoms, government advisory measures, online consultation facility, and dynamics of disease. This app implemented crowdsourcing approach by which general public members enter their details for self-assessment, and this assessment is then used to trace the infectious contacts or agents as a digital contact tracing concept. This app uses location services to geolocate the users and Bluetooth to maintain the log of contacts when one user/device comes in contact with another user/device, and as such, digital contact tracing activity helps in identifying the cluster of diseases and communities which are at risk of infection. The Aarogya Setu app was downloaded by ~ 100 million users within 40 days of its launch (Upadhyay 2020), and by using app's crowdsource data, the Indian government detected approx. 13,000 positive cases, informed 130,000 probable users of being at risk, and identified 300 potential clusters (The Times of India).

Numerous digital contact tracing apps are in use in different parts of world—TrackCOVID (Yasaka et al. 2020), TraceTogether (Bay et al. 2020), WeTrace (De Carli et al. 2020), and Google and Apple's recently announced joint initiative (Li and Guo 2020).

COVID-19 Data Visualization and Exploratory Data Analysis

With early experiences of epidemics such as 2002–2003 SARS-CoV (Boulos 2004) and the 2012–2014 MERS-CoV (Gikonyo et al. 2018), and other seasonal flu's, online real-time or near-real-time mapping of diseases' occurrences using geospatial technologies and web applications have always been used as a pivotal web-based tools in tracking

health threats and combating infectious diseases. This section described a range of mapping dashboards based on geospatial technologies for tracking and unfolding the coronavirus disease around the world. Some of the global and national geospatial initiatives with an aim to supply information faster than diseases are as summarized in Table 1.

Infectious Diseases Modelling

The intention of infectious diseases surveillance is to detect epidemics in their early stages so that the countermeasures could be taken for preventing its wide spread. Such surveillance tasks require many epidemiological and statistical methods with geospatial features in investigating epidemics, preferably from localized areas. The reason for preferring the local areas for investigation is because epidemics generally emerged in small areas and then spread widely, if they are not controlled. However, some methods require rigorous conventions in their underlying models and are too problematical to be applied on small areas. Therefore, this section discusses simple methods for detecting diseases prevalence with case studies on small datasets which would be more useful for public health activities.

Clustering

Clustering deals with the study of spatial-temporal patterns of the spread of communicable diseases and identification of other disease-related aspects allied with heterogeneous geographical distribution which might be helpful in elucidating the diseases' spread mechanism. Such study and analysis on space-time patterns is a kind of disease surveillance which involves detecting the outbreak clusters of active cases, monitoring of localisation and isolation of infectious agents, and relative risks assessment of affected sites at early stage (Clements et al. 2013; Cromley 2019; Kulldorff 2001). This study on geographical clustering of infectious diseases with temporal features helps in making strategies that dynamically update on emergence source of disease outbreak to help epidemiologists and decision makers for identification of spread and risk zones. Thus, clustering helps to enable timely prevention and containment measures and timely resource allocation to mitigate the diffusion of diseases.

Based on space-time surveillance of diseases, space-time scan statistic (Kulldorff 1997) is one of the cluster detection tools which is widely used in geographical surveillance of diseases during epidemic and/or pandemic. The space-time scan statistic comes with two versions—prospective and retrospective (Desjardins et al. 2018;

Table 1 Summary table for geospatial dashboards for COVID-19

Project name	Datasets	Scope	Purpose
WHO Coronavirus Disease (COVID-19) Dashboard (Dong et al. 2020) (https://covid19.who.int)	WHO's official data	Global	Visualization of official daily counts of confirmed cases and deaths related to COVID-19 with time stamps using Esri ArcGIS Online service Exploratory data analysis using 3D graph to perform country-wise analysis using population, confirmed cases, cumulative cases, deaths and cumulative deaths Provides daily aggregate case and death count in CSV
Johns Hopkins University COVID-19 Dashboard (Dong et al. 2020) https://coronavirus.jhu.edu/map.html)	Aggregated data from WHO, European Centre for Disease Prevention and Control (ECDC), Worldometers, BNO News, US CDC, IPoint3Arces, COVID Tracking Project and DXY	Global	Dashboard for visualizing real-time mapping of COVID-19 with graphs on confirmed and daily cases Critical trend analysis on new cases per day, mortality and fatality analysis in population, timeline of outbreak, etc.
ISRO's BHUVAN COVID-19 Geospatial Solution (https://bhuvan-app3.nrsc.gov.in/corona/corona_dashboard/dashboard/dashboard.php?type=citizen)	COVID-19 data (Source: MoHFW)	India	Time series visualization of active, recovered and deceased cases from March 26 to till date Graphical analysis on spread trend of COVID-19 day-wise and state-wise
COVID19INDIA (https://www.covid19india.org)	CM, Health M) handles, Press Trust of India, state press bulletins, PBI and ANI reports	India	Visualization of cumulative and daily numbers of confirmed, active, recovered, deceased and tested state-wise cases through maps and graphs Provides daily COVID-19 cases in state and district, and cases reassigned to states through API
MapmyIndia COVID-19 (https://maps.mapmyindia.com/corona?districts_containment_zone,containment_zone_gradient)	COVID-19 data (Source: MoHFW) Hunger Relief Centres (Source: MyGov) Hunger & Night Shelter (Source: MyGov, NDMA)	India	Provides API on corona dashboards to visualize cases at district and state level, hotspots, treatment centres, testing labs, quarantine centres, containment zones, lockdown issues, hunger relief, hunter and night shelters
Monthly climate explorer for COVID-19 (https://cds.climate.copernicus.eu/apps/c3s/app-c3s-monthly-climate-covid-19-explorer)	Monthly COVID-19 cases (Source: JHU CSSE) Atmospheric composition—PM ₁₀ and NO ₂ (Source: CAMS EAC4) Meteorological data—humidity (1000 hPa) and surface air temperature on hourly and monthly average rate (Source: ERA5 reanalysis)	Global	Visualization of COVID-19 fatalities with climatic and atmospheric variations on monthly basis Exploratory analysis on correlation of pollutants and specific humidity with COVID-19 deaths
Experimental COVID-19 and Global Seismic Risk Map (https://maps.openquake.org/map/covid-19-2020-05-20v3-grm/#2/34.9/0.0)	COVID-19 cases (Source: JHU CSSE) Global earthquake risk map (Source: GEM Global Earthquake Model)	Global	Visualize earthquake as a cause of increase in COVID-19 cases due to people's displacement from damaged buildings

Owusu et al. 2019), and difference between both is that prospective neglects historical clusters which may have previously occurred before the most current time period of analysis with no health threat (Kulldorff 2001). Therefore, the prospective version of space-time scan statistic is commonly used to detect statistically significant active or evolving clusters of diseases for the present time period,

and when more data become available, the tool can be re-run to detect new evolving clusters with update on relative risks for each affected sites. Previously, the prospective space-time scan statistic was used in thyroid cancer (Kulldorff 2001), shigellosis (Jones et al. 2006), measles (Yin et al. 2007), syndromic surveillance (Yih et al. 2010), and many other diseases. However, cluster analysis of

diseases can be performed through several packages and libraries in R (Gómez-Rubio et al. 2005) and Python software (Yeng et al. 2019).

The contribution of cluster detections and analysis in COVID-19 pandemic is becoming useful nowadays as it detects active and emerging clusters of COVID-19 and notify epidemiologist, decision makers, and public health care officials, which can help in eradicating infections from affected sites, and improving interventions, quarantine, and isolation measures. The significant applications of clustering with respect to infectious diseases modelling are demonstrated across the world (Zarikas et al. 2020), for example, India (Bhosale and Shinde 2020), USA (Desjardins et al. 2020; Hohl et al. 2020), Brazil (Martines et al. 2020), Italy (Cereda et al. 2020), China (Ji et al. 2020; Liu et al. 2020a, b; Qiu et al. 2020; Zhang et al. 2020), Singapore (Bhosale and Shinde 2020; Pung et al. 2020), South Korea (Shim et al. 2020), French Alps (Danis et al. 2020), Germany (Pfefferle et al. 2020), Sergipe (Andrade et al. 2020), etc.

Outlier Analysis

The outlier is defined by Hawkins (1980) as “an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism.” In other words, when data generation process starts behaving abnormal and reflects the abnormalities or errors in data, such abnormalities are known as outliers (Bansal et al. 2016). However, the outliers generally hold advantageous information about the systems unusual characteristics and entities, which impact the data generation process. Some of the useful applications of outliers in diseases are (Cleynen et al. 2016; Dai and Bikdash 2016; Krishnan et al. 2017; Lo et al. 2015; Prensner et al. 2011; Washington 2007; Wu and Krishnan 2010). Clustering algorithms are optimized to find clusters rather than outliers, and the accuracy of outlier detection depends on how good the clustering algorithm captures the structure of clusters.

Maximum Entropy Modelling (Maxent) Approach

In context of disease systems, disease transmission risks depend on distribution of pathogens (species) in space and time in some complex environmental conditions (Townsend 2015), and as such treatments are focused mainly on spatial dimensions; therefore, diseases transmission risks are purely handled through geographical phenomena. Such geographical link with diseases leads to the challenge of spatial mapping of disease transmission which overcame through the branches of biodiversity science—ecology and biogeography. Such approach of ecological and biogeographical modelling can be seen from various studies on disease

transmission risks mapping, for example, Arboleda et al. (2009), Deka and Morshed (2018), Ferreira et al. (2020), Holt et al. (2009), Mweya et al. (2013), Nakazawa et al. (2013), Reeves et al. (2015), Samy et al. (2014), Qian et al. (2014), Zhao et al. (2016), Zhu et al. (2017).

Following recent studies on geographical mapping of pathogens causing disease transmission, machine learning-based maximum entropy method (Maxent) (Elith et al. 2011; Phillips 2010) is applied on spatial records of COVID-19 with a set of 19 bioclimatic environmental variables from WorldClim (Poggio et al. 2018; Ramírez Villegas and Bueno Cabrera 2009) to analyse their favourable environmental conditions (as shown in Fig. 1 and Table 2), required in maintaining its population. The Maxent principle is to estimate the target probability distribution by applying the maximum entropy to distribution which is most spread or closest. This study is carried out in R software (Ihaka and Gentleman 1996), and a geographical dataset consists of latitude and longitude of those regions which were affected till March, 2020.

Figure 1 depicts the habitat suitability map of virus with probability range in colour scale to visualize the high suitability (light and dark green colour), medium suitability (yellow and dark brown), low suitability (light brown colour) and unsuitable (grey colour). Table 2 lists the favourable bioclimatic variables and their contribution in percent in maintaining the suitability of virus.

Susceptible-Infectious-Recovered (SIR) Model

Epidemiology deals with the study of pattern and occurrence of diseases in space and time associated with other factors such as environment demography, and the translation of epidemiology into mathematical equations to describe the spread of infectious diseases is known as mathematical epidemiology (Allen et al. 2008; Rayner and Bender 1980). The mathematical epidemiology model is implemented to understand the transmission dynamics of communicable diseases by categorizing population into susceptible, infectious, and recovered compartments. The first basic model, known as Susceptible-Infectious-Recovered (SIR) model, was proposed by Kermack and McKendrick (1991) to describe the transmission of epidemic diseases from individual to individual. The SIR model is a set of nonlinear ordinary differential equations, which is mathematically defined as follows:

$$\frac{dS}{dt} = \mu(N + S) - \beta SI \quad (1)$$

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

$$\frac{dR}{dt} = \gamma I - \mu R \quad (3)$$

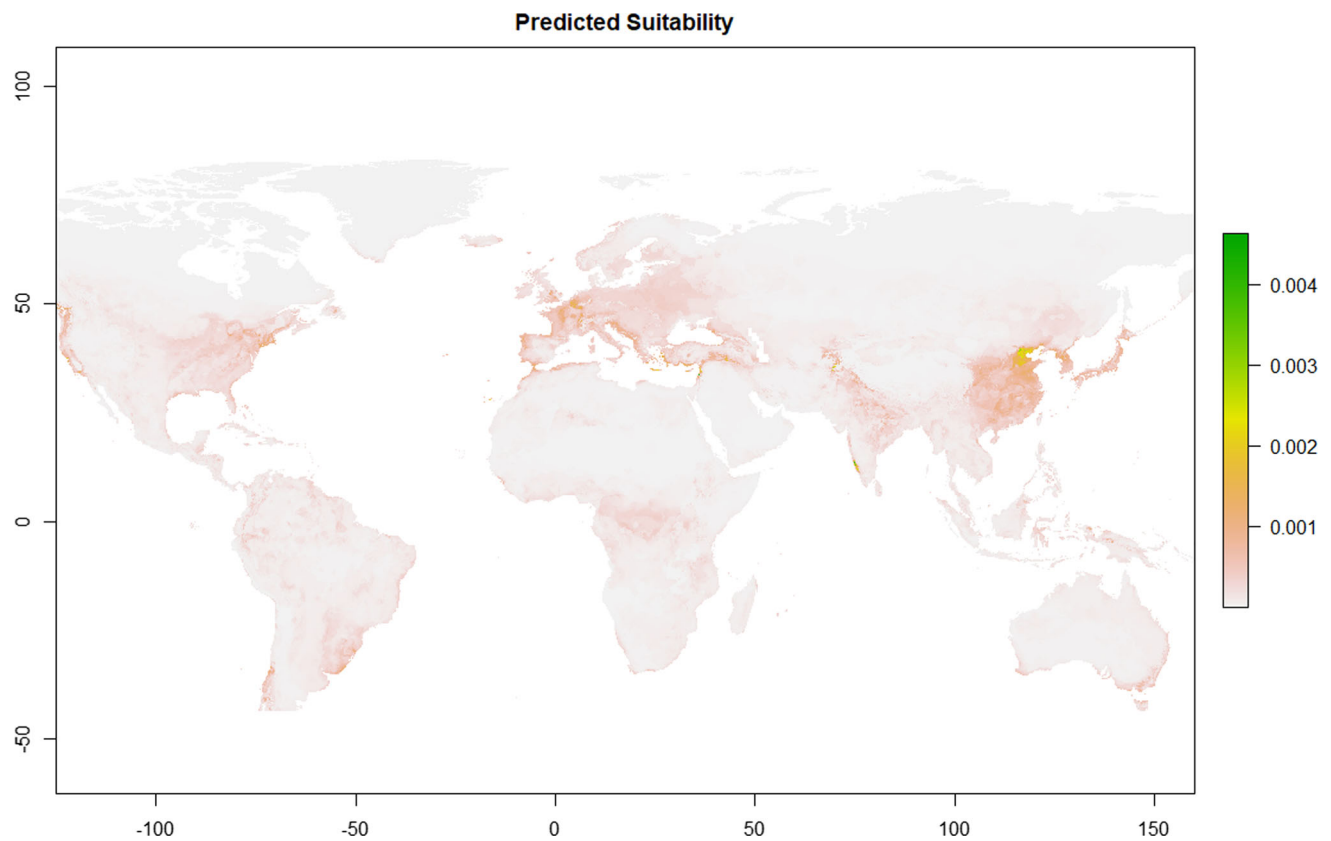


Fig. 1 Predicted suitability of *Betacoronavirus* using data till March, 2020

Table 2 Responsible bioclimatic variables in suitability modelling

Bioclimatic variables	Percent contribution
Mean temperature of coldest quarter	22.3
Precipitation of wettest month	14
Mean diurnal range	13.2
Isothermality	8.8
Annual mean temperature	8.2
Max temperature of warmest month	5.9
Precipitation of coldest quarter	5
Precipitation of wettest quarter	4.2
Annual precipitation	3.2
Precipitation of driest quarter	2.6
Mean temperature of driest quarter	2.6
Mean temperature of wettest quarter	2.4
Precipitation seasonality	2.4
Temperature seasonality	1.6
Precipitation of warmest quarter	1.4
Mean temperature of warmest quarter	1.1
Temperature annual range	0.7
Precipitation of driest month	0.5
Min temperature of coldest month	0.1

Here,

- S is the class of susceptible individuals who are not yet contracted to disease,
- I is the class of infectious people who are now infected with disease and become infectious to infect others,
- R is class of recovered individuals who have recovered now and are removed from class S ,
- N is a total population size, $N = S + I + R$, and t is time in days or weeks
- β is the contact rate of infected person with suspected person per day,
- γ is the infectious period and average infectious period is $1/\gamma$,
- μ is the per capita death rate which is adjusted by birth rate μN .

There are many other compartment models derived from the basic epidemic model, (SIR), with more compartments and transitions—(1) Susceptible-Exposed-Infectious-Recovered (SEIR) (Li and Muldowney 1995), (2) Susceptible-Infectious-Exposed-Recovered-Dead (SEIRD) (Piccolomiini and Zama 2020), (3) Susceptible-Infectious-Exposed-Recovered-Susceptible (SEIRS) (Liu and Zhang 2011), (4) Susceptible-Infectious-Quarantine-Recovered (SIQR) (Erdem et al. 2017), etc.

The SIR model is implemented for COVID-19 to understand its dynamics of transmission from individual to individual in India for first 25 days of this pandemic. The data on actual cases of COVID-19 are obtained from COVID-19 India (<https://www.covid19india.org/>) and then used in SIR model in R software. The SIR model is optimized using parameters, $\beta = 0.00021$ and $\gamma = \frac{1}{14}$, against actual cases of disease (Fig. 2), and then, the probable SIR model is constructed using the above parameters for next 90 days to understand that how much of the population could be infected in upcoming days, as shown in Fig. 3. However, the SIR model can be constructed and optimized for more days by increasing the population size and decreasing the contact rate.

Google Earth Engine

Google Earth Engine (GEE) is a web-based free cloud computing platform introduced by Google, Inc., to provide a high-performance geospatial computing platform with multi-petabyte analysis-ready remote sensing big data (Casu et al. 2017; Gorelick et al. 2017). The GEE has opened an intrinsically parallel processing way for the researchers to swiftly process millions of satellite images

by reducing massive computations. GEE provides a dynamic web explorer for data cataloguing, visualization, and analysis in JavaScript (Goodman 2007) and Python (Oliphant 2007). Also, GEE provides a time-lapse video tool for measuring, tracking, and visualizing changes to the Earth's surface over the past 35 years (1984–2018). Some applications of GEE can be seen in time series analysis of snakebites (Reis et al. 2020), forest cover (Hansen et al. 2013; Johansen et al. 2015), tree cover loss (Tracewski et al. 2016), surface water (Donchyts et al. 2016; Pekel et al. 2016; Tang et al. 2016), populated areas (Patela et al. 2015), cropland and soils (Padarian et al. 2015; Xiong et al. 2017) and various applications (Dong et al. 2016; Joshi et al. 2016; Lee et al. 2016).

COVID-19 affects respiratory system of humans (Marini and Gattinoni 2020; Rothan and Byrareddy 2020; Xu et al. 2020), and based on previous studies, this can be more prone to those who are in old age (Wu et al. 2020), smoking habits (Liu et al. 2020a, b), respiratory complications (Chen et al. 2020; Sohrabi et al. 2020) due to long-term exposure to harmful pollutants. For instance, NO_2 is one of the harmful air pollutant gases which might be responsible for causing chronic obstructive pulmonary disease (COPD) (Abbey et al. 1993; Euler et al. 1988),

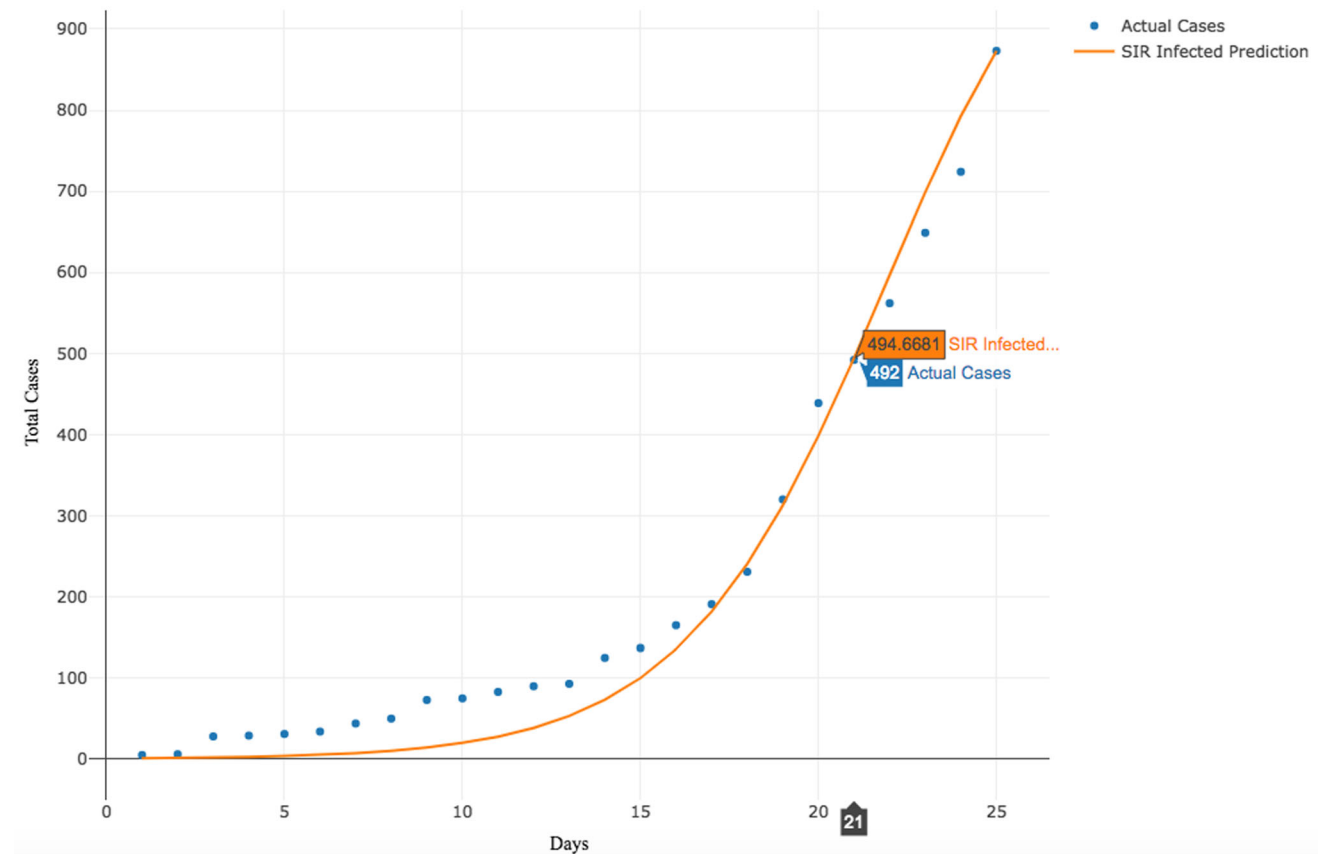


Fig. 2 Model optimization as per actual cases for first 25 days

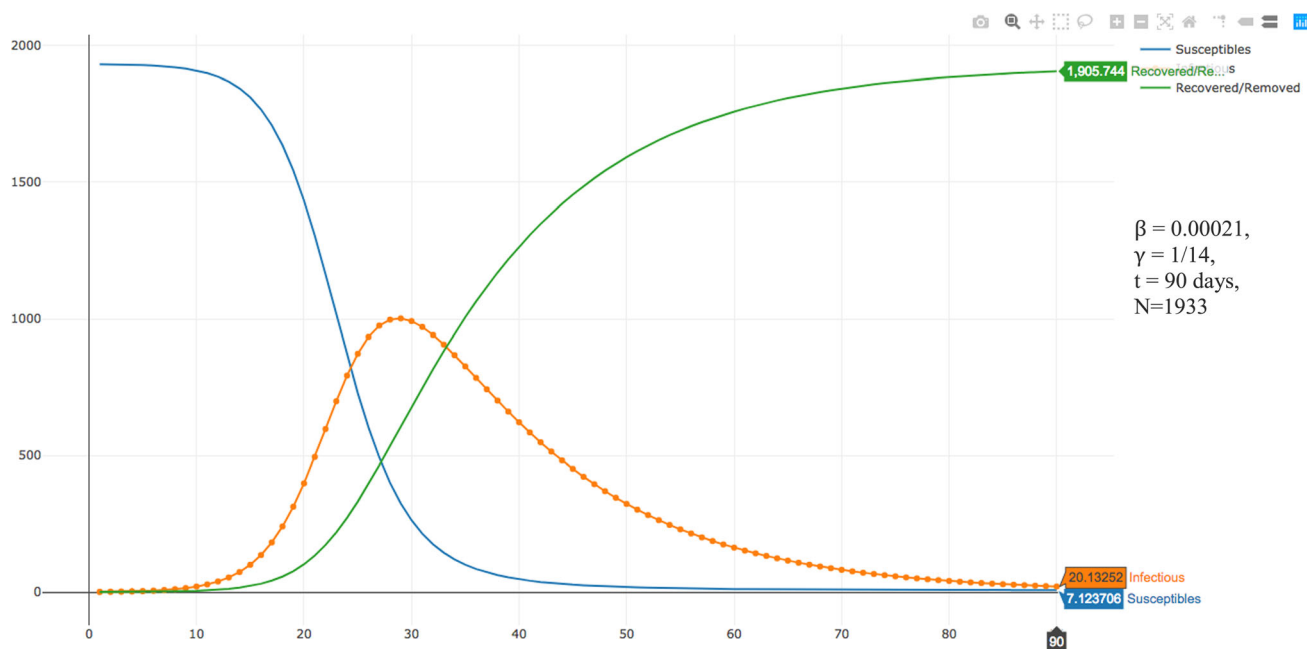


Fig. 3 SIR model for 90 days

hypertension (Shin et al. 2020), heart diseases (Gan et al. 2012; Mann et al. 2002), diabetes (Shin et al. 2020), lung injuries (Bowatte et al. 2017), and even death in humans, which can make them susceptible to various respiratory viruses or syndromes. In the current pandemic situation, many studies are carried out to analyse that NO_2 could be one of the responsible factors for COVID-19 fatality (Baldasano 2020; Dutheil et al. 2020; Frontera et al. 2020; Kumari and Toshniwal 2020; Nakada and Urban 2020; Ogen 2020; Pansini and Fornacca 2020; Ranjan et al. 2020; Zoran et al. 2020).

Hotspot and Coldspot Analysis

The aim of many geosurveillance systems or surveys is to find hazard level of the subject, which can be later converted to risk. The idea of risk mapping is to assign a probability value to the occurrence of defined condition indicating some form of unusual aggregation in spatial information (Jeefoo et al. 2011; Osei and Duker 2008). The spatial clustering of high values is known as hotspot, whereas the cluster with low values is known as coldspot (Jana and Sar 2016). With advancements in GIS, the hotspot (or coldspot) detection method is widely used in disease surveillance system (Ahmad et al. 2015; Bhunia et al. 2013; Jana and Sar 2016; Jeefoo et al. 2011; Ng et al. 2018; Osei and Duker 2008; Panahi et al. 2020; Willerson et al. 1981). In the current pandemic situation, various studies were carried out on detecting hotspot as well as coldspot in different countries to fight against it, for example, Al-

Jumaili and Hamed (2020), Arab-Mazar et al. 2020, Bouffanais and Lim (2020), Eckerle and Meyer (2020), Mo et al. (2020).

With the help of such disease modelling algorithms, various tasks are carried out for surveillance of current pandemic, and some of them are summarized in Table 3.

Capacity Building

The online capacity building and outreach programme was organized at Indian Institute of Remote Sensing (IIRS), Dehradun, to make public aware about application and services of geospatial technology, and various mathematical and statistical modelling tools for automated analysis on infectious disease surveillance and control. The programme on geospatial technology in conjunction with COVID-19 was held during June 15–19, 2020, on the topic “Health GIS: Geoinformatics for COVID-19” with 3601 participants from 494 institutions and universities (https://www.youtube.com/watch?v=_I09X4jdbfg&t=29s). The lectures were delivered on role of geospatial technology, mobile and web GIS in COVID 19 pandemic, public health surveillance system, geo-processing for public health, disease risk mapping, exploratory data analysis, and dynamic epidemiology modelling (<https://www.youtube.com/watch?v=u2UOGCgTlo4&t=269s>).

Table 3 Summary table of geospatial epidemiology modelling for COVID-19

Author	Methodology	Findings	Study area
<i>SIR model</i>			
Toda (2020)	Data collection on COVID-19 cases from JHU CSSE All countries whose confirmed cases exceeds 1000 as on March 27, 2020 and initial cases exceeds 10 Parameter estimation as per actual COVID-19 cases SIR model development using estimated parameters	Estimated transmission rate, fraction of infected individuals at peak, number of days to reach the peak, fraction of population that would be infected and standard error Predict the course of disease and helped in mitigating the peak	All countries
<i>Clustering</i>			
Pung et al. (2020)	Confirmed COVID-19 patients examined for epidemiological, clinical and demographic data Queried about possible contact with overseas patients Reported median incubation period	Identify first three clusters of COVID-19 cases on Feb 3, Feb 5, and Feb 8, 2020 Identify secondary transmissions in the respective clusters	Singapore
<i>Maxent</i>			
Ren et al. (2020)	Location of COVID-19 cases from Beijing, Guangzhou, Shanghai, and Shenzhen Nine socioeconomic factors were collected and categorized into population density, public transportation, daily necessities demands, and medical assets for diagnosing the COVID-19 infection Ecological Niche Modelling for COVID-19 infection risk zones using Maxent Validation of niche models	In Beijing, Guangzhou, and Shenzhen., numbers of infected groups, average cases per infected group, and percentage of imported cases from outside regions decreased from 21st Jan to 27th Feb Clustering in Beijing and Guangzhou was reason for COVID-19 infection risks influenced by heavy population density	China

Conclusions

This comprehensive review on geospatial technology and services for infectious diseases surveillance is to illuminate the path for decision makers and public health officials for implementation of web-based spatio-temporal health information system and epidemiological modelling tools. Geospatial technology is having rich set of tools for understanding spatial and temporal aspects in wide range of disciplines, dominantly in geospatial health research for establishing the links between diseases and in its suitable environment. Also, this provides various geo-statistical approaches to perform analysis in finding the interconnectedness spatial and temporal links, outbreak detection, identifying population at risk, movement tracing of infectious agents, investigation of environmental factors responsible in outbreak, and hotspot and coldspot analysis of outbreak location. However, there are many mathematical modelling algorithms also used for estimating the prevalence and incidence rate of disease, proportion of population that would be infected at any particular time, and severity and potential scale of epidemic or pandemic. Such analytical capable information systems are for automated visualization and analysis of every dimensions of infectious disease related to its transmission, demographic and environmental recognitions, and statistics. This review

paper concluded that geospatial applications and dynamic modelling algorithms could offer a well-timed solution to all time historic challenge of humankind in understanding the disease outbreaks, vulnerabilities to population health and adaption of upcoming generation.

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