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Role of big geospatial data in the COVID-19 crisis

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1. Introduction

The subject of geography has often been understood and considered as the gazetteer with names of countries and information about them but this stream of knowledge has turned out to be the most important addition to the meaning and metaphors of our daily life from driving a car to identifying the critical hotspots/clusters of any disaster. “Space” forms the kernel and core of geographic knowledge, thus encompassing the phenomenon of body politics and social fabric in its entirety. In contemporary times, with emerging paradigms of “space episteme,” this intersection and contestation of topos with the active political space in the public discourse has been rightly epitomized by Edward Soja as the “spatial turn” [1] of this century. The world has changed drastically in the spheres of climate, production, consumption, and behavioral patterns with imbalances and negative feedbacks being observed in the environment, which prompted some scientists to propose the present epoch as “Anthropocene” [2]. Geography studies this changing interaction of environment with the human responses in its comprehensive theoretic and scientific mechanism and subsequently models the impacts and patterns of this dynamic trend.

Diffusion of diseases and the related outbreaks have also been modeled and the pathways have been tracked, thus helping the world and regional health agencies to frame policies and strategies for mitigating the impact and spread of diseases. As currently the world is in the grip of the deadly and sporadic pandemic disease named by the WHO as coronavirus disease 2019 (COVID-19) [3] and the virus as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [4] by the International Committee on Taxonomy of Viruses, geographic knowledge coupled with temporality of the incidence and spatial prevalence of this global health threat have proved to be the guiding light among the dark frontiers of novel epidemiologic characters of this outbreak. Currently the rate of infection is rising and with more than 300,000 deaths [5], there is an increasing need of using the hybrid technologies at individual, regional, and global levels

for containing the spread of this threatening public health disaster. In view of the same, different datasets, both small and big, are integrated in order to have an effective strategy and policy interventions derived from the applications of both. Although the concept of big data was making rounds around 1990s, it gained prominence in public knowledge in 2008 [6]. From the past decade, we have seen the overarching influence of data science and big data analytics with the intersection of different computing, statistical, and visualization media [7]. The past decade has seen the rapid emergence of big data and data science research, which lies at the intersection of computer science, statistics, and data visualization and builds on the growing wealth of digital footprints. Big data is a term that generally deals with the computational analysis of large datasets either in an individual environment or with integration methods for predictive and forecast studies of phenomenon. Its uniqueness lies in its “gathering and data generation capacities on an enormous scale and precision” [8]. Public health management and data science have been revolutionary with the introduction of big geospatial data with its distinct character of having the three “V” values of volume, veracity, and velocity, with respect to storing data, accuracy, and speed [9]. Cisco’s forecast records that data traffic is expected to reach 930 exabytes by 2020, a sevenfold growth from 2017 [10]. Traditionally, public health data aggregation systems lacked the comprehensive reach and individual trajectories of disease patterns while using the manual registers and coded data, which was both time consuming and expensive exercise with confined geographic limits.

A vast amount of literature deals with the relevance of big geospatial data in the epidemiologic threats that regions have faced [11], analyzing the “big data” approach in gathering digital data on health while using both medical and participatory symptomatic data with individual or geographic scales in clusters. The data from nonhealth categories is also interfaced through social media platforms and Google analysis with location, travel, and behavioral patterns, thus giving real-time information about the incidence and transmission of the disease. The “big data” was applied in the Ebola virus outbreak in West Africa and Middle East respiratory syndrome (MERS) outbreak in South Korea by using real-time geolocation data coupled with the public health data repository for identifying the transmission chains in order to cope up with the shortage of data amidst the spread of these diseases [12]. This strategy of “digital epidemiology” [13] turns out to be the useful approach in rapid response and in times of scarce resource regions and crisis situations with limited transmission analysis and delayed reports. Ginsberg et al. [14], in their path-breaking study, developed Google Flu Trends (GFT) a web-driven service started in 2008 that monitored and mined data from millions of Google users for tracking and modeling the incidence and spread of influenza cases by combining the data from the Center for Disease Control and Prevention (CDC) and laboratory-confirmed cases. With the real-time analysis similar to weather forecasting, predictions from GFT were 97% accurate in comparison with CDC data, and GFT was able to forecast regional influenza outbreaks before they were reported by the CDC at least by 10 days. Guerrisi et al. [8] studied participatory surveillance “Influenzane” by using

Sentinel's satellite data with spatial variables for reporting influenza. The volunteers have to self-sign in online for recording their health status on a weekly basis with its swath even to diseases beyond infectious ones.

Mohr et al. [15] makes the analogous perspectives on epidemiologic models with particle physics by taking into account the uncertainty in human behaviors against the deterministic signatures of physics resulting in complex disease forecast. Liu et al. [16] introduced a novel simulation dynamics of pandemics and visualization "EpiDMS" used during healthcare emergencies with real-time scenario building. This tool aims to fill an important gap in decision-making during healthcare emergencies by generating near-real-time projections and simulations of an emerging pandemic trajectory. These simulation studies have the provision of generating actionable research for epidemiologic modelers and experts of public health.

2. Materials and methods

In this chapter, we discuss the ways in which big geospatial data has been applied to the COVID-19 crisis and how it helped in actionable decision support system and timely data handling by using both health and nonhealth data at both user and geographic levels. This study aims to discuss the innovative and novel technologies that have been applied in this COVID-19 crisis in the geospatial realm, from artificial intelligence to machine learning algorithms. Using the representative geospatial visualisation acting as the informative and well-researched platforms as the data sources for coping up with the COVID-19 crisis. We would be using the case studies of China and Taiwan as in how these countries have applied the computational architecture of big geospatial data and location analytics surveillance techniques for predicting and monitoring positive cases. Both these countries have largely been successful in reducing the impacts of COVID-19 by smartly handling and applying big geospatial data in critical hotspot areas and breaking the transmission of the spread further. We strictly tracked the official websites around the world to collect the epidemiologic information about the COVID-19 pandemic. With the help of literature extraction analysis from different secondary research sources, this study would evaluate the relevance of big geospatial data in COVID-19 crisis in both these countries and around the world.

3. Background

Data generated from Earth observation and simulation tools deal with a huge interface of data production daily in tera- to petabytes [17]. Big geospatial data representing unprecedented information can be leveraged for adding value to better engineering development, scientific research, and healthcare decisions [18]; for envisioning general understanding of the Earth systems; and for improving our lives [19], as in Fig. 30.1. Geospatial data primarily revolves around the spatial analysis and classification about

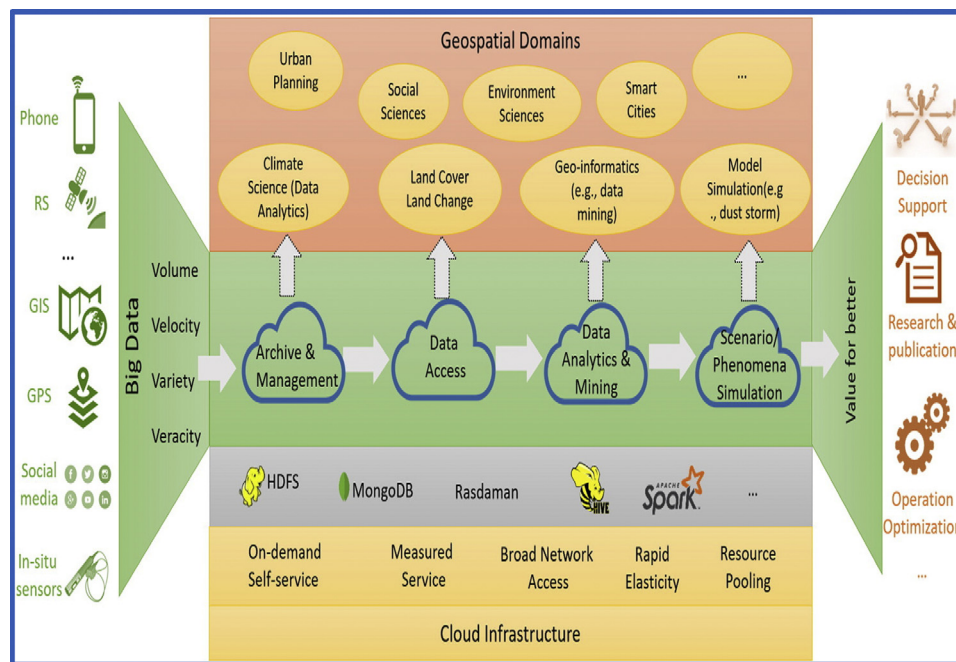


FIGURE 30.1 Architecture of geospatial data. GIS, geographic information systems. Adapted from C. Yang, M. Yu, F. Hu, Y. Jiang, Y. Li, Utilizing cloud computing to address big geospatial data challenges, *Comput. Environ. Urban Syst.* 61 (2017) 120–128. <https://doi.org/10.1016/j.compenurbsys.2016.10.010>.

events, objects, or phenomena having an element of embedded location. The location can have dynamic (outbreak of an infectious disease) or static (point location of a road) basis; this information is then collated to attribute and temporal data for having the cumulative impact of any event. In the geospatial data since the volume of satellite data became public, initially there were major challenges [20]. Remote sensing is the fundamental method in any research field for gathering data Earth surface [21]. Remotely sensing data provides emergency support services and management in real-time basis [22,23] having enhanced spatial resolution [24] and precise estimations. Geospatial data when integrated with sensor technologies provides more inclusive ways of generating natural and socioeconomic data [25]. For example, the satellite imageries of the earth observation data with the Internet of Things advancing the capabilities of monitoring and scientific evaluation of the natural and biophysical environments [26,27]. With growing digital footprints of human actions, hybrid studies of both qualitative and quantitative assessments are needed [28] as inclusion of dualistic crowd-sourced data and social media could mark the historic event in scientific research in terms of availability of data [29]. The facilitation of Spatial Data Infrastructure (SDI) in the geospatial data sharing from local to global stakeholders has resulted in users accessing, retrieving, and spreading related geospatial information and metadata in a

safe environment [30]. Regarding the same, the Fog-based SDI framework *GeoFog4Health* was developed and assessed named for mining geohealth big data and geoinformatics analytics in Maharashtra, India, for malaria-positive cases [31].

4. GeoAI: geospatial artificial intelligence and health geographics

The combination of artificial intelligence (AI) and geographic information systems (GIS) integration gives way to GeoAI as a promising science for its significance in healthcare geographies [32]. Adopting the methodology of retrospective data analysis, “probable” patients having the virus are tracked immediately with the help of location analytics and travel information of the patient (Fig. 30.2). We can improve our understanding of viral transmission by using the movement data with the help of GeoAI, which would help countries in taking necessary steps for suppressing the impact of virus. China introduced AI in real-time prediction of the infected COVID-19 cases across China [33] helping in tracking and monitoring the further outbreak and

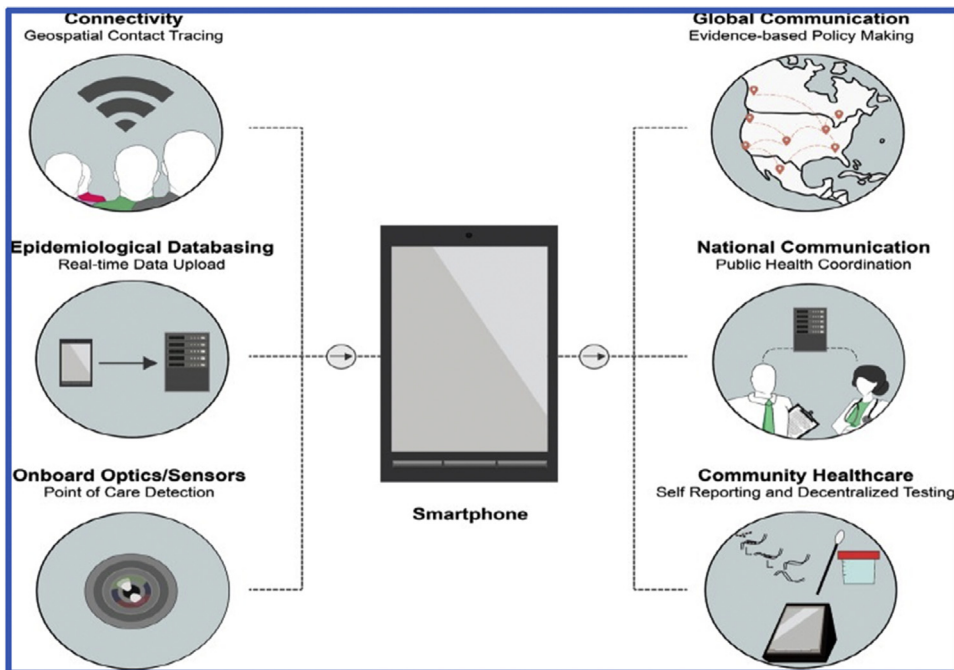


FIGURE 30.2 An artificial intelligence-based framework using mobile phones for COVID-19 diagnosis and surveillance. Adapted from Q. Pham, D.C. Nguyen, T. Huynh-The, W. Hwang, P.N. Pathirana, *Artificial intelligence (AI) and big data for coronavirus (COVID-19) pandemic: a survey on the state-of-the-arts*. Preprints (2020). <https://doi.org/10.20944/preprints202004.0383.v1>.

improvement of policy and health scenario. A study [34] depicts how big geospatial data recorded real-time infectious cases particularly in Wuhan city where the virus was first discovered. This study further gives the timeline of cases with travel history, age, and gender and hospitalization and discharge details, and the fascinating part of this research is how all the documented cases were geo-tagged with accuracy even at the building level.

Deep learning neural networking of GeoAI was used in the United States at both regional and city levels in GFT, and climate variables from the National Climatic Data Center were used for infectious disease modeling using tools of artificial tree algorithm. Using the personal sensing analytics, GeoAI collects data from the sensors embedded in mobiles and wearables [15]. GeoAI with the help of geospatial energetics could be used to analyze this location analytics and to determine which activity with spatiotemporal configurations with respect to health outcomes. Application of this integrative metadata and satellite imagery aids in a robust GIS and comprehensive geo-database in an analysis-ready format opening a new path for redefining epidemiologic studies in concert with the pathways and vector-based differentiations across the world. The use of data mining and machine learning algorithms like Python and Anaconda with the integration of geographic knowledge can help us in the accurate and reliable prediction of threats and stresses whether related to health or environment. Google Earth Engine uses this algorithm-based geographic and environmental variables for predicting and subsequently providing effective management strategies for a better and sustainable biophysical and social environment. The Centre on Climate Change and Planetary Health of the London School of Hygiene and Tropical Medicine links infectious disease data and modeling tools with environmental and climate change and develops early warning systems from the earth observation satellite data. For identification risks derived from environmental and spatial factors, geostatistical and algorithmic methods are applied for evaluating their impact on infectious disease trajectories.

5. Big geospatial data and infectious disease pattern

In this age of big data, the need of “big geospatial data” becomes equally important, given the complexities and dynamic nature of biophysical and social interfaces. While struggling for containing COVID-19, geospatial technology spearheaded in providing the datasets for prevention and breaking the transmission chain with detection of socio-spatial response. Related to geographic location, this data generally is used for mapping and storage purposes with topological and coordinated mechanism. With the advances in geospatial techniques for environmental and public leading to robust and effective database management, spatial analysis, and mapping of patterns in disease diffusion and prevalence cases. Fog computing is then subsequently used for health geoinformatics. Field data and mapping are the commonly used techniques, and the novel streams of “big data” from mobile users and social media are being studied for translating the repository of patient geolocations into coordinates for their spatial positioning

and analyzing the trends of epidemiology, sociopsychologic inclinations, and infectious diseases. Many research groups and institutions have started different informational systems, with query building on potential virus transmission routes such as “mobility queries”, “fever clinics,” and “epidemic geo-map” visualizations with the existing software logistics resulting in timely awareness and geographic control of the virus [35], as in Fig. 30.3.

The spatiotemporal behaviors of infectious diseases are very large in densely populated areas and the related systematic complexities pose great challenges for modeling them [36].

In the same vein, geospatial knowledge has helped in the real-time information delivery and public understanding of coronavirus spread around the world. Most of the geospatial data platforms have been in the forefront currently for data visualization and monitoring and concurrently has reached the common people in any place of the world and at any time. The WHO (Fig. 30.4) has provided the situational dashboard updated every 15 min providing a real-time perspective for officials and users with easy-to-view visual interface using GIS Science on regional and case-wise spread.

The enhanced and sophisticated real-time information can be viewed through the Environmental Systems Research Institute (ESRI). The ESRI Disaster Response Program and ESRI’S ArcGIS Hub (Fig. 30.5) including the in-depth information from various operational dashboards with interactive data view provide key understanding and monitoring of global and feature datasets related to the virus and public knowledge.

Another platform where the expert epidemiologic analysis of COVID-19 hyphenated with the public health analytics has been maintained by the Center for Systems Science and Engineering at Johns Hopkins University (JHU) (Fig. 30.6) with its own GIS operational setup mapping the similar trajectory in real time.

In India the MapmyIndia Maps and Move app enabling users to locate, view, and reach testing laboratories nearby and subsequent isolation and treatment facilities. Users can have firsthand account of the facilities and can add reviews of the centers there and help other users with updated and critical knowledge regarding the conditions and status of quarantine and isolation facilities. MapmyIndia (Fig. 30.7) resources are designed for early detection and isolation of infected persons, which are crucial in respect to the spread of this disease.

In Germany, Maxar, the new space company, with geospatial technology built layered data software for disease modeling, including facilities, demographics, mobility patterns, etc. Maxar’s Human Landscape (Fig. 30.8) data utilizes multiple datasets for the production of metadata and undertakes mission reconnaissance.

In response to the coronavirus (COVID-19) pandemic, Blue Marble Geographics (Fig. 30.9) has generated different layers of spatial GIS data sources for mapping the spread of the disease. It includes streaming and downloadable sources, which are updated and monitored on a daily basis. Blue Marble will also make public customized templates to assemble and order the data for cumulative data analysis.

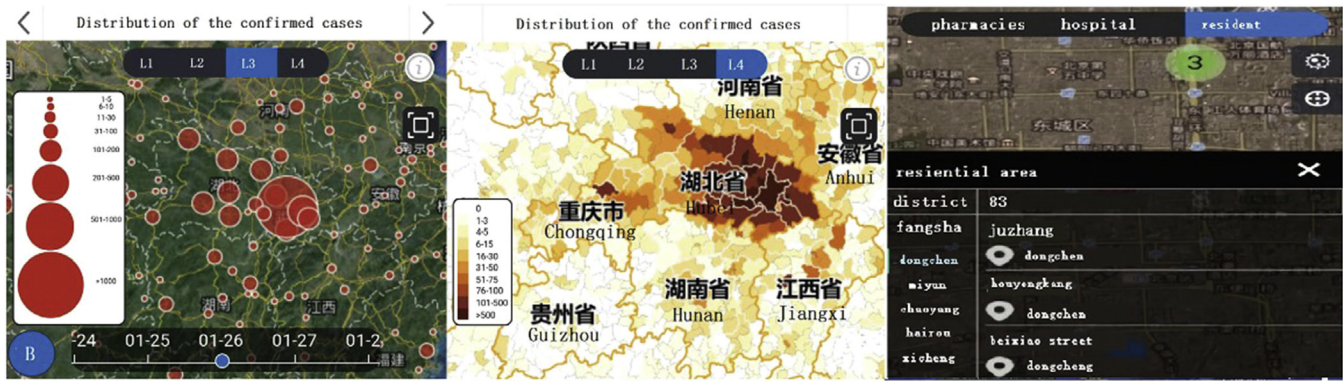


FIGURE 30.3 The China Academy of Information and Communications Technology (CAICT): 2020 dynamic information query system for different scales: (A) city level, (B) county level, and (C) community level.

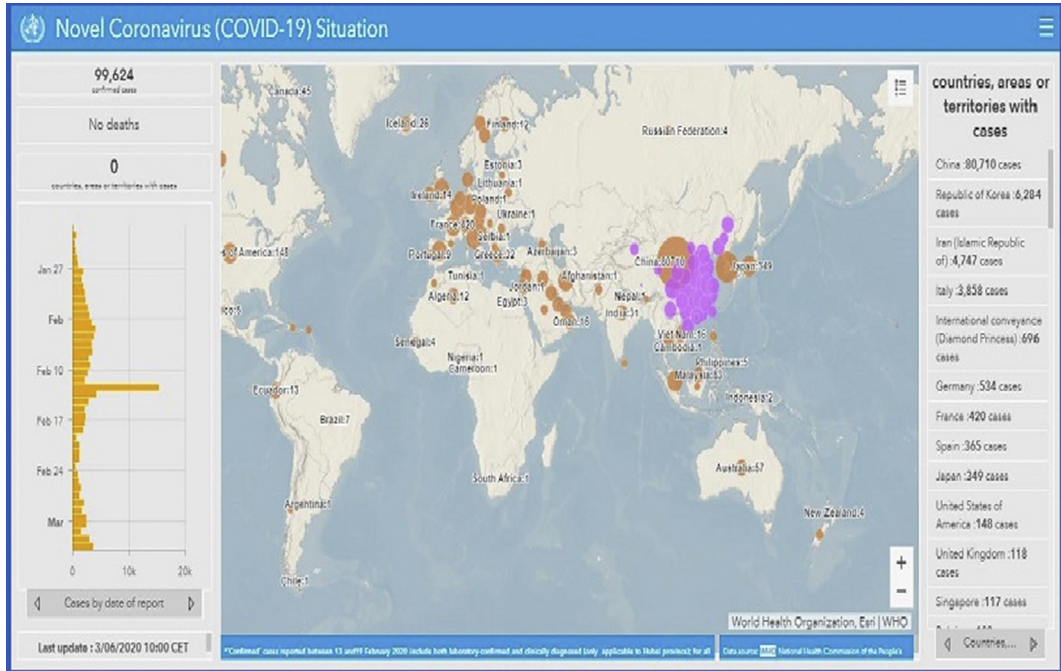


FIGURE 30.4 The WHO novel COVID-19 situation visualization.

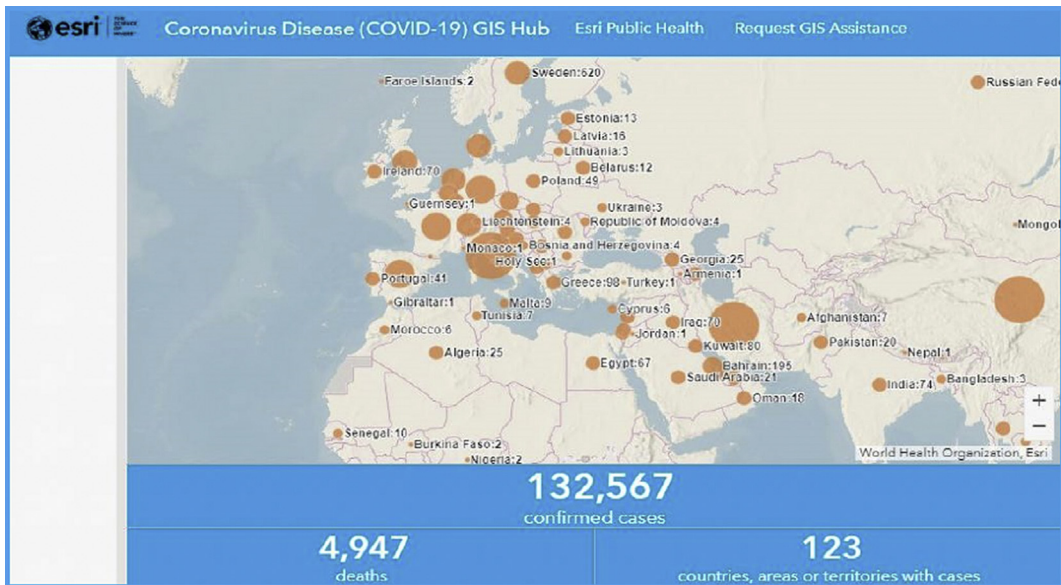


FIGURE 30.5 The Environmental Systems Research Institute (ESRI) ArcGIS Hub.

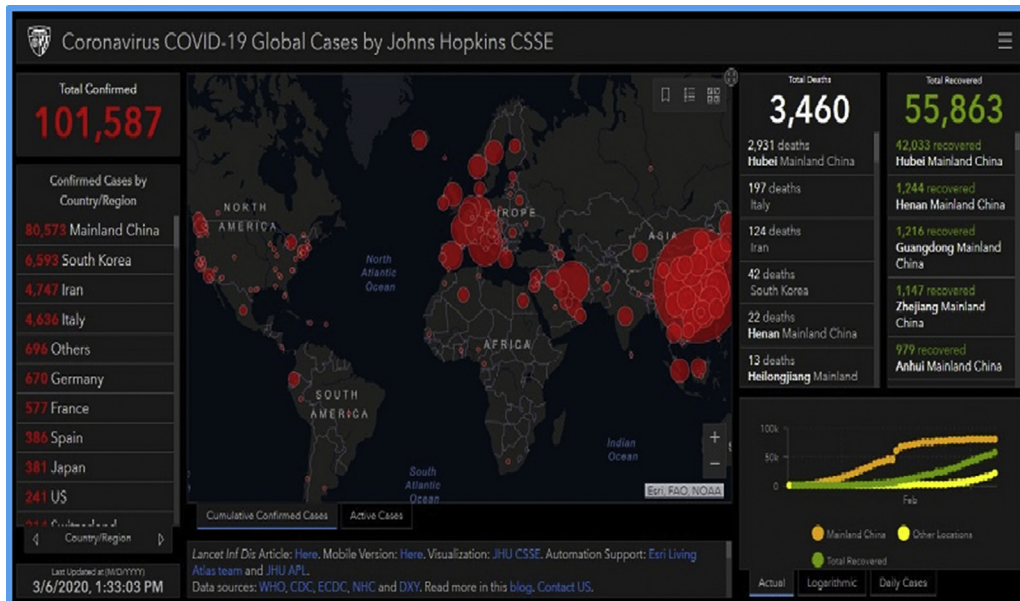


FIGURE 30.6 TheCenter for Systems Science and Engineering at Johns Hopkins University (JHU).

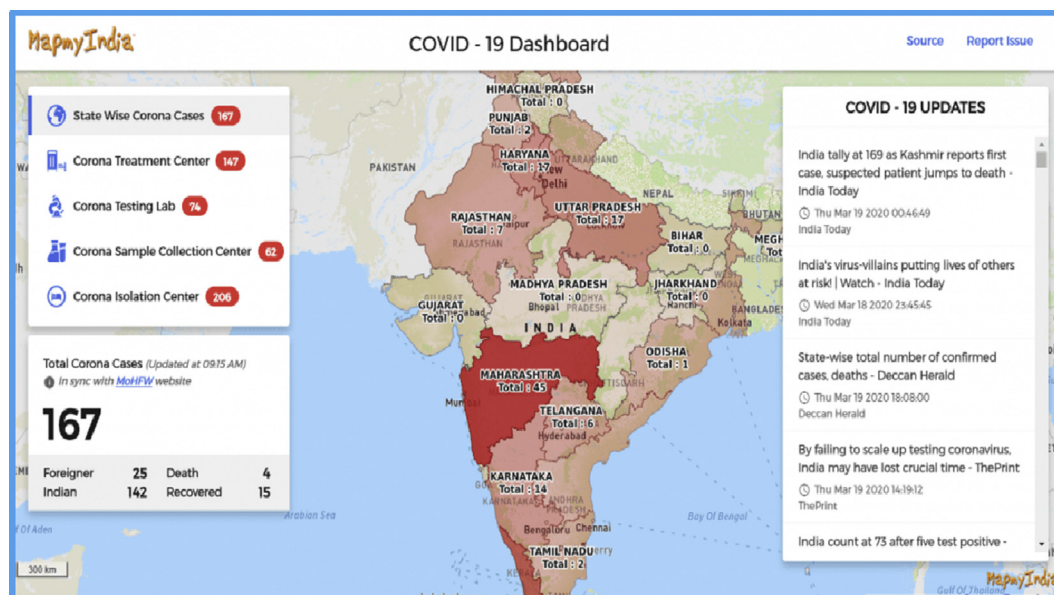


FIGURE 30.7 TheMapmyIndia coronavirus dashboard.



FIGURE 30.8 Maxar's human landscape software.

6. Case studies of China and Taiwan

Big geospatial data technologies played a crucial role during COVID-19 in China by using positioning system driven by BeiDou country's own GNSS constellation by tracking patients and critical hotspots and thus successfully controlling the spread and analyzing the patterns of the outbreak. China has always made use of its geospatial prowess in the crisis situations having a higher degree of technical and scientific data [37] and to support the government for judging the epidemic scenario and devising control and prevention measures [38]. With precision mapping and satellite imagery with reliable data, China built the two new makeshift facilities for treating patients across the country. BeiDou-enabled drones were also used for monitoring crowded public spaces and emergency tests were sent to more than 6 million geo-connected vehicles using this constellation. The Chinese Ministry of Transportation was able to swiftly send emergency messages to over 6 million connected vehicles and also deliver medical services in hospital areas using BeiDou.

From Figs. 30.10–30.13, it is clearly visible how China smartly applied the geospatial knowledge for the coronavirus pandemic. TFSTAR, a second-generation AI satellite designed by the Satellite Technology Research Center of University of Electronic Science and Technology of China (UESTC) and ADA-Space, used powerful processing and

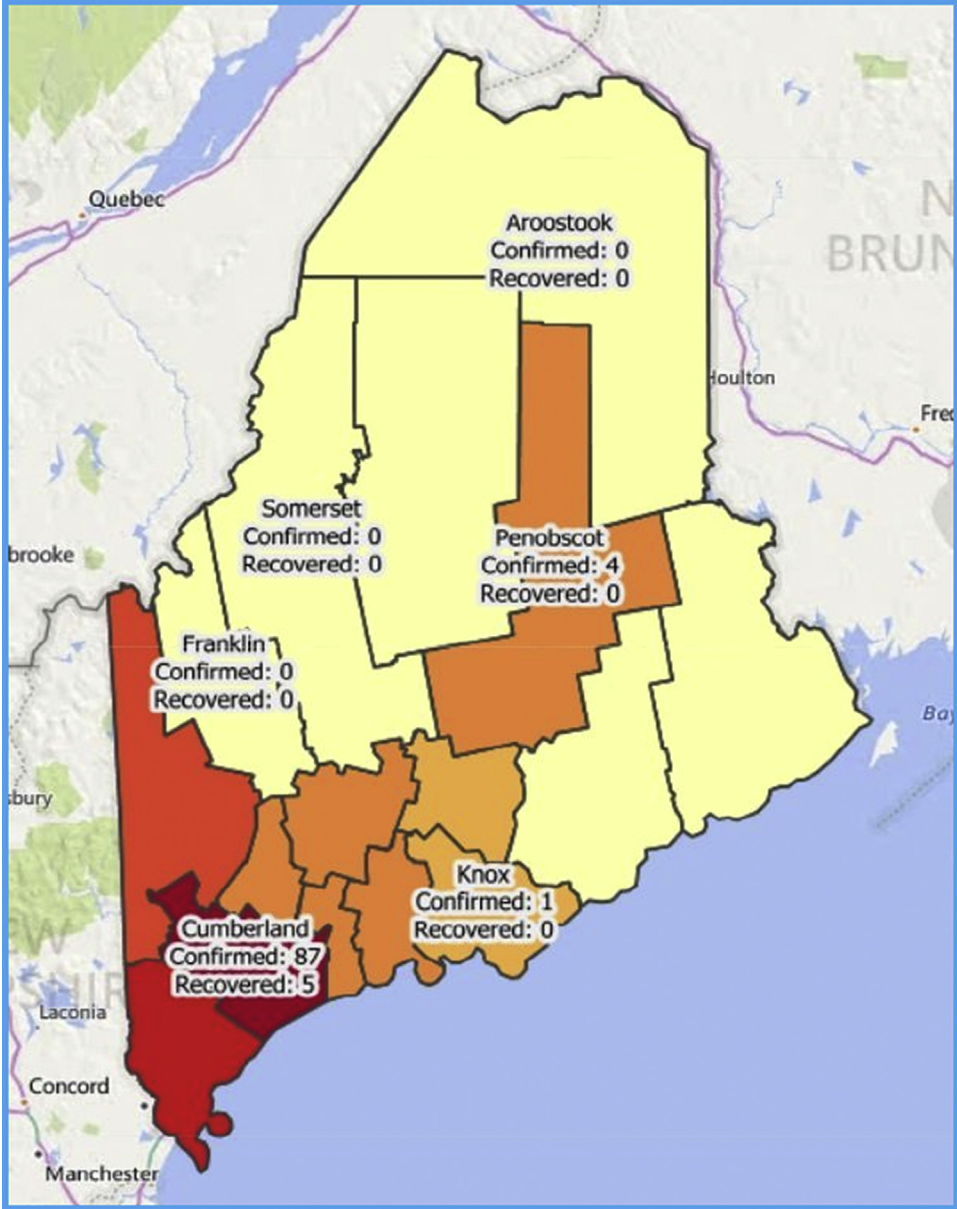


FIGURE 30.9 Blue Marble's data sources.

analytics [39] enabling it to sift through this geospatial data. Utilizing TFSTAR's geocoding data with its advanced processing capabilities, health geoinformatics of COVID-19 was generated where geographic proximities of active cases were easily visualized.

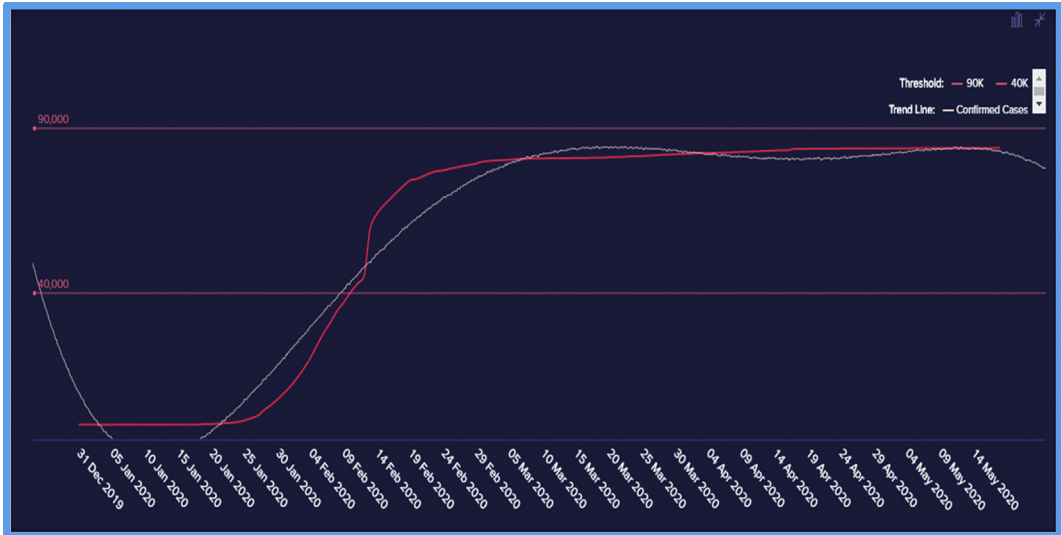


FIGURE 30.10 Confirmed cases daily trend.

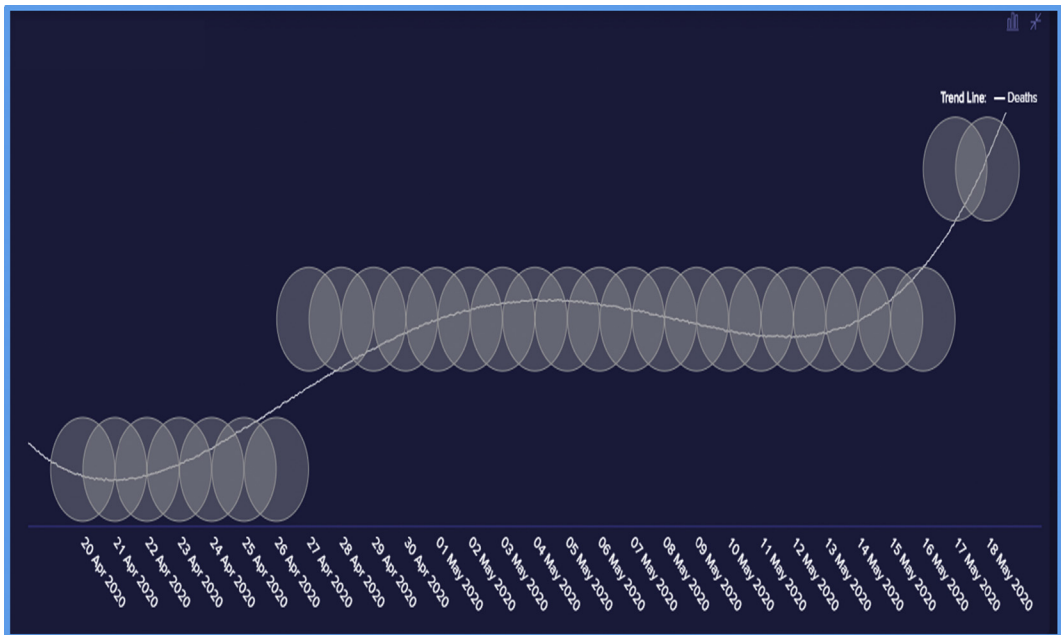


FIGURE 30.11 Daily death trend in China.

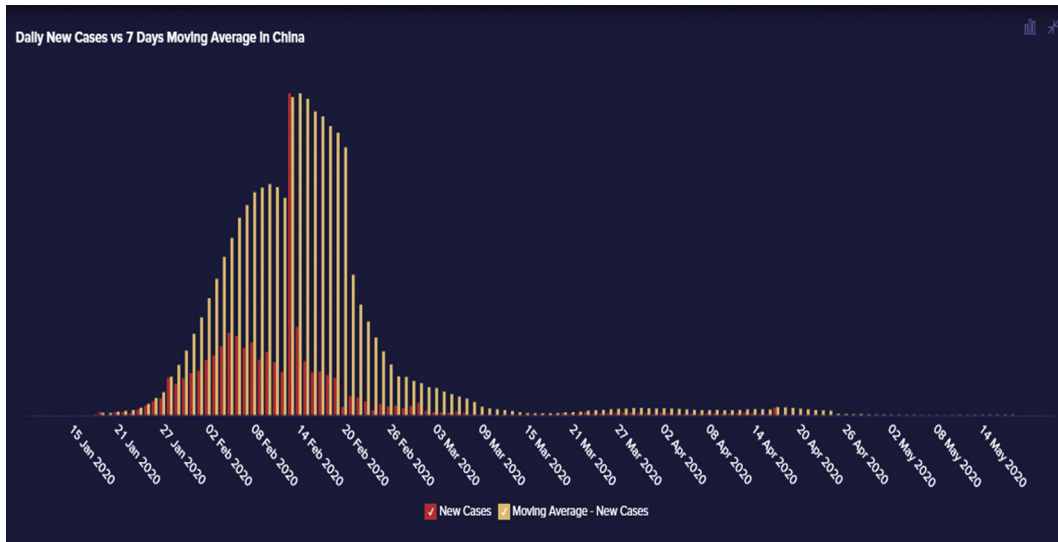


FIGURE 30.12 The 7-day moving average of daily new cases in China.

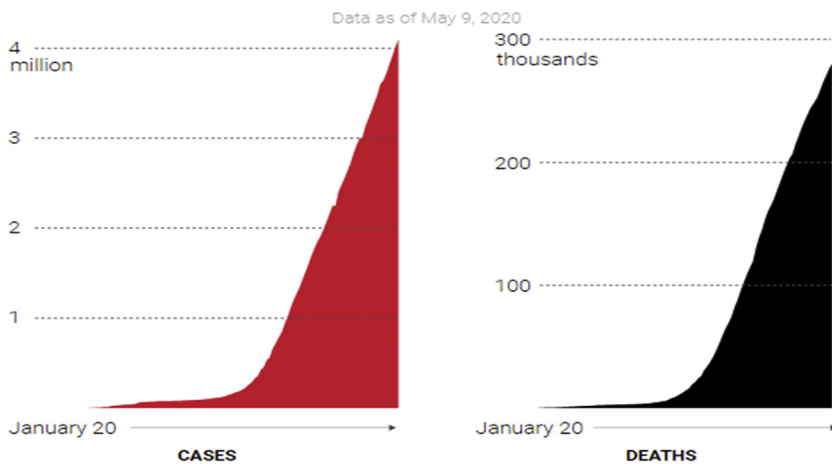


FIGURE 30.13 Daily cases mortality of coronavirus.

6.1 Taiwan and geospatial governance

Using the SARS outbreak [40] in dealing with the threat of this emerging threat too, from the very first case, Taiwan started onboard quarantine protocol for travellers who came from Wuhan. Taiwan organised a response team for COVID-19 on January 2, 2020, and activated the Central Epidemic Command Center (CECC) [41] on January 20 for integration of various datasets in containing the pathway trajectory of the epidemic. Taiwan was considered one of the most at-risk areas outside mainland China owing to its transport links, close proximity, and trade relations [42]. Taiwan used the hybrid detests

of health and demographic data and used the geospatial fencing technique [43] for keeping track and monitoring the impact of COVID-19 pandemic and using info-epidemiologic data in making people aware about the daily events. Home-quarantined cases were tracked through GPS for tracking their movements so as to prevent transmission.

7. Results and discussions

From the analysis of data carried out in both China and Taiwan, there is clearly a positive trend of COVID-19 showing a drastically decreasing pattern, as shown in the Figs. 30.13–30.15. China in its earlier spatial outbreak was having the peak curve of daily cases (Fig. 30.10), but with the application of big geospatial data and aggressive location analytics based testing and quarantine protocols, it successfully managed to contain the pandemic and simultaneously flattened the curve (Fig. 30.12). Taiwan on other hand replicating the reading of the 2003 SARS outbreak started the preemptive geospatial governance measures for keeping COVID-19 at bay. While it was generally considered that Taiwan will be most hit by this pandemic, with the robust and coordinated geospatial driven governance measures, Taiwan turned out to be the model for nations in managing this public health crisis. As Taiwan saw the spike in infection rates early on (Fig. 30.15) but from the onset of February, there was a decline in the reported cases, as they were the first to use mobile phones for tracking purpose (Figs. 30.16–30.18). Both the countries paved way for other countries in the efficient management and control of COVID-19, further validating the relevance of geospatial data and its ubiquity in facing

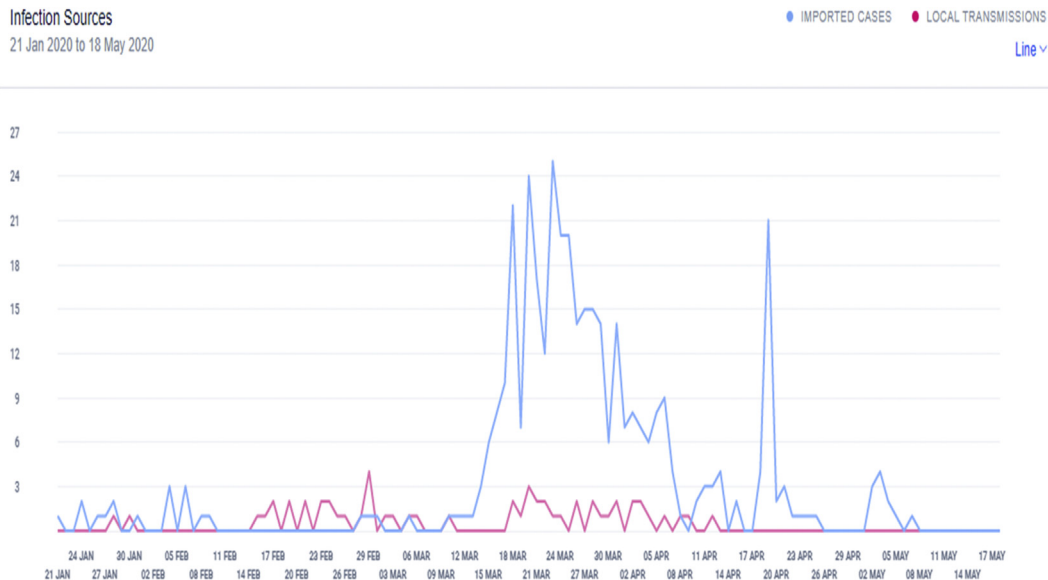


FIGURE 30.14 Infection sources in Taiwan.

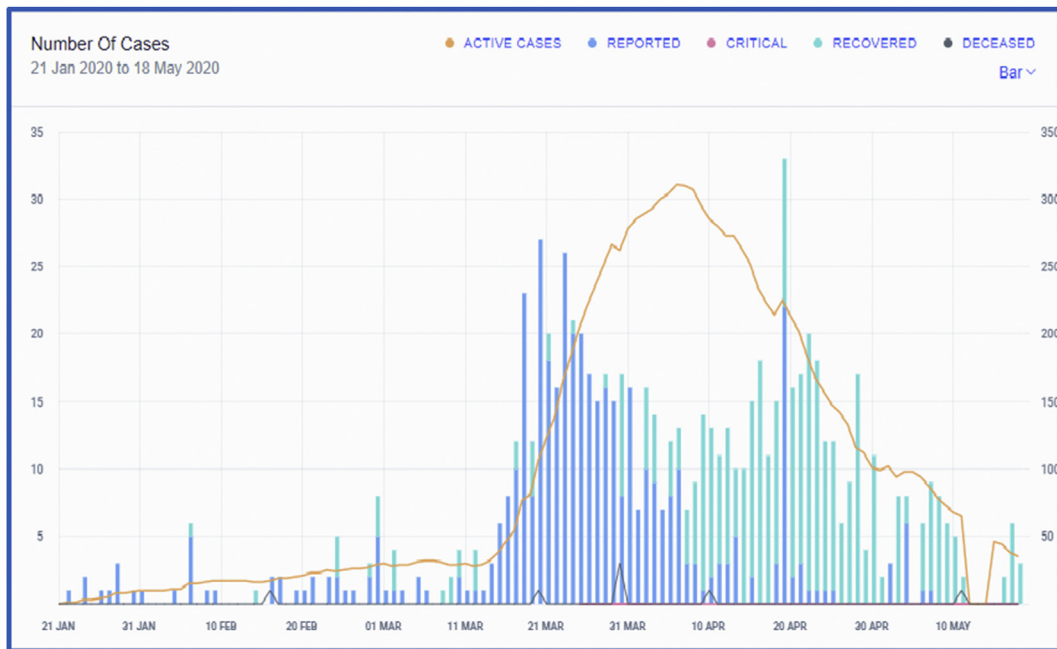


FIGURE 30.15 The number of cases from January 21, 2020, to May 18, 2020.

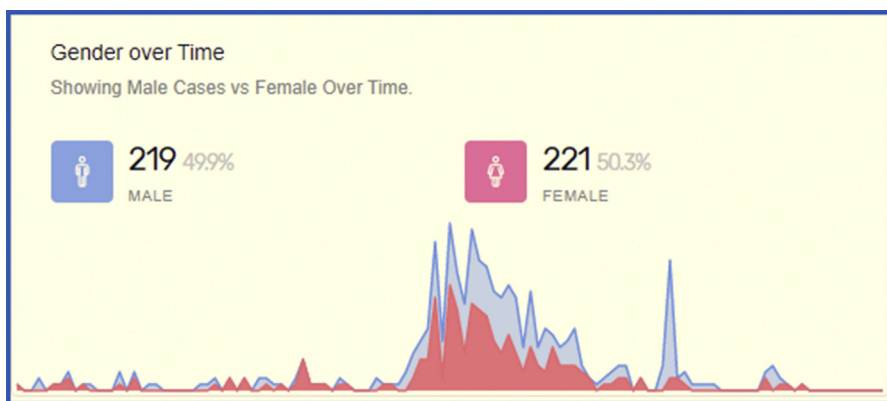


FIGURE 30.16 Gender over time cases.

the “crisis situations” from healthcare emergencies to natural disasters. Big geospatial data has been rightly called as the golden thread of the fourth Industrial Revolution [44] in the governance and policy strategies for intersectional abilities of public datasets and geospatial data sources.

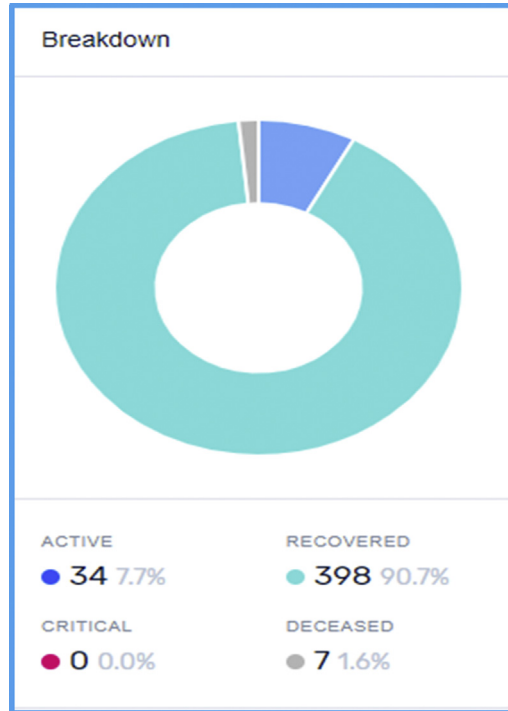


FIGURE 30.17 Breakdown of cases.

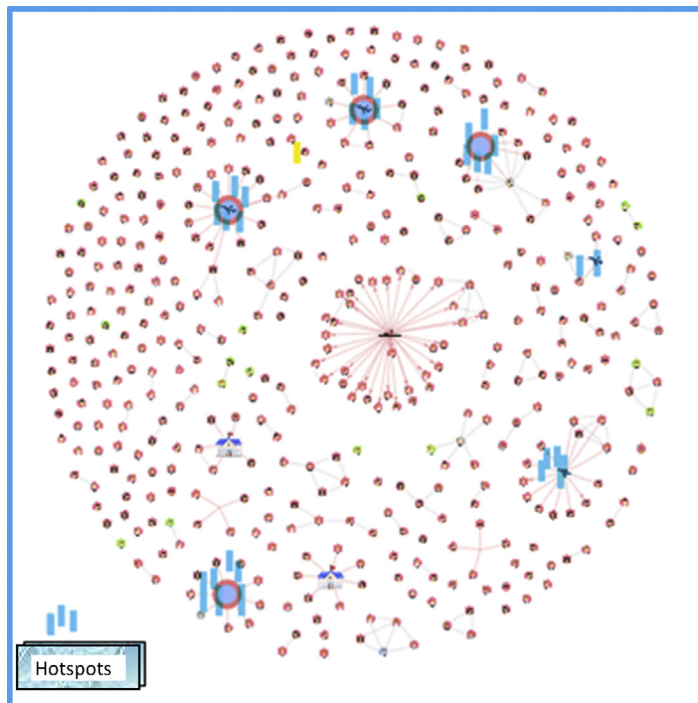


FIGURE 30.18 Network analysis of cases.

8. Conclusion

There is an immediate need to move beyond the traditional epistemes of geographic analysis and to explore further the added value of geospatial data for our research in disease ecology, health inequalities, and spatial diffusion. Taking the example of the southern region of Kerala, India (world's model for containing COVID-19) [45] with its first COVID-19 case mass collated mobilization drive was carried out with the surveillance data and affected areas, everything was then geo-tagged and mapped in the immediate tracing exercise with hotspots being delineated by using “big geospatial data.” Many examples of “critical geographies” can be cited from the fact that institutions, organizations, and governments have undermined the character and configurations of “geographic data” when it comes to health infrastructure and individual healthcare facilities; thus coronavirus has laid bare the response and system of approach of countries around the world. There are widespread inequalities when it comes to the healthcare geographies around the world, thus intensifying a need for global and uniform approach of healthcare governance in consonance with the changing contours of political and economic landscapes around the world.

There is an emerging role for big geospatial data in healthcare studies as geography forms the quintessential component of both regional and individual health, and coupled with relevant satellite, remote sensing, and individual data, it has traversed the boundaries of disciplines, having its applications in infectious diseases, social, behavioral, and genetics. Thus big geospatial data coupled with integration and prediction of disease behaviors (with high spatiotemporal resolution) for newly emerging role of machine learning in spatial data helps in dealing effectively with the “crisis” of environmental or health nature. Furthermore, big geospatial data can be harnessed for tracking the new research frontiers in disease etiology and provide new perspectives in the emerging risk factors of epidemiologic research.

References

- [1] B. Warf, Spatial Turn, in: *The Wiley-Blackwell Encyclopedia of Social Theory*, 2017, pp. 1–3. <https://doi.org/10.1002/9781118430873.est0533>.
- [2] D. Carrington, *The Anthropocene Epoch: Scientists Declare Dawn of Human-Influenced Age*, 2016. <https://www.theguardian.com/environment/2016/aug/29/declare-anthropocene-epoch-experts-urge-geological-congress-human-impact-earth> (Accessed 8 May 2020).
- [3] WHO: World Health Organization, *Coronavirus Disease (COVID-2019) Situation Reports*, 2020. [https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-\(covid-2019\)-and-the-virus-that-causes-it](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it) (Accessed 20 April 2020).
- [4] A.E. Gorbalenya, S.C. Baker, R.S. Baric, et al., The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2, *Nat. Microbiol.* 5 (2020) 536–544, <https://doi.org/10.1038/s41564-020-0695-z>.
- [5] Worldometers, 2020. <https://www.worldometers.info/coronavirus/>. (Accessed 16 May 2020).

- [6] S. Lohr, How Big Data Became So Big, *The New York Times*, 2012. <http://www.nytimes.com/2012/08/12/business/how-big-data-became-so-big-unboxed.html>. (Accessed 5 May 2020).
- [7] Wikipedia, Big Data, 2015. https://en.wikipedia.org/wiki/Big_data. (Accessed 10 May 2020).
- [8] C. Guerrisi, C. Turbelin, T. Blanchon, et al., Participatory syndromic surveillance of influenza in Europe, *J. Infect. Dis.* 214 (Suppl. 4) (2016) S386–S392.
- [9] B. Marr, Why Only One of the 5 Vs of Big Data Really Matters, 2015. <http://www.ibmbigdatahub.com/blog/why-only-one-5-vs-big-data-really-matters>. (Accessed 8 May 2020).
- [10] W. Shei, Almost One Zettabyte of Mobile Data Traffic in 2022 – Cisco, 2019. <https://telecoms.com/495666/almost-one-zettabyte-of-mobile-data-traffic-in-2022-cisco/>. (Accessed 10 May 2020).
- [11] S. Bansal, G. Chowell, L. Simonsen, A. Vespignani, C. Viboud, Big data for infectious disease surveillance and modeling, *J. Infect. Dis.* 214 (Suppl. 4) (2016) S375–S379.
- [12] G. Chowell, J.M. Cleaton, C. Viboud, Elucidating transmission patterns from internet reports: Ebola and Middle East respiratory syndrome as case studies, *J. Infect. Dis.* 214 (Suppl. 4) (2016) S421–S426. <https://doi.org/10.1093/infdis/jiw356>.
- [13] M. Salathé, L. Bengtsson, T.J. Bodnar, D.D. Brewer, J.S. Brownstein, C. Buckee, et al., Digital epidemiology, *PLoS Comput. Biol.* 8 (7) (2012) e1002616. <https://doi.org/10.1371/journal.pcbi.1002616>.
- [14] J. Ginsberg, M.H. Mohebbi, R.S. Patel, L. Brammer, M.S. Smolinski, L. Brilliant, Detecting influenza epidemics using search engine query data, *Nature* 457 (2009) 10124. <https://doi.org/10.1038/nature07634>.
- [15] D.C. Mohr, M. Zhang, S.M. Schueller, Personal sensing: understanding mental health using ubiquitous sensors and machine learning, *Annu. Rev. Clin. Psychol.* 13 (2017) 23–47.
- [16] S.H. Liu, S. Poccia, K.C. Candan, G. Chowell, M.L. Sapinz, EpiDMS: data management and analytics for decision making for epidemic spread simulations, *J. Infect. Dis.* 214 (Suppl. 4) (2016) S427–S432.
- [17] C. Yang, R. Raskin, M. Goodchild, M. Gahegan, Geospatial cyber infrastructure: past, present and future, *Comput. Environ. Urban Syst.* 34 (4) (2010) 264–277.
- [18] J.G. Lee, M. Kang, Geospatial big data: challenges and opportunities, *Big Data Res.* 2 (2) (2015) 74–81.
- [19] V. Mayer-Schönberger, K. Cukier, *Big Data: A Revolution that Will Transform How We Live, Work, and Think*, Houghton Mifflin Harcourt, 2013.
- [20] J. Li, D. Agarwal, M. Humphrey, C. Ingen, K. Jackson, Y. Ruy, “eScience in the cloud: a MODIS satellite data reprojection and reduction pipeline in the Windows Azure platform, in: *Parallel & Distributed Processing (IPDPS)*, IEEE International Symposium on, Atlanta, GA, April 19–23, 2010.
- [21] D. Lu, The potential and challenge of remote sensing-based biomass estimation, *Int. J. Rem. Sens.* 27 (7) (2006) 1297–1328. <https://doi.org/10.1080/01431160500486732>.
- [22] D.M. Tralli, R.G. Blom, V. Zlotnicki, A. Donnellan, D.L. Evans, Satellite remote sensing of earthquake, volcano, flood, landslide and coastal inundation hazards, *ISPRS J. Photogramm. Remote Sens.* 59 (4) (2005) 185–198. <https://doi.org/10.1016/j.isprsjprs.2005.02.002>.
- [23] R. Cossu, E. Schoepfer, P. Bally, L. Fusco, Near real-time SAR-based processing to support flood monitoring, *J. Real-Time Image Process.* 4 (3) (2009) 205–218. <https://doi.org/10.1007/s11554-009-0114-4>.
- [24] P. Treitz, P. Howarth, High spatial resolution remote sensing data for forest ecosystem classification an examination of spatial scale, *Remote Sens. Environ.* 72 (3) (2000) 268–289. [https://doi.org/10.1016/S0034-4257\(99\)00098-X](https://doi.org/10.1016/S0034-4257(99)00098-X).

- [25] C.-Y. Chong, S.P. Kumar, Sensor networks: evolution, opportunities, and challenges, *Proc. IEEE* 91 (8) (2003) 1247–1256. <https://doi.org/10.1109/JPROC.2003.814918>.
- [26] P. Defourny, C. Vancutsem, P. Bicheron, C. Brockmann, F. Nino, L. Schouten, M. Leroy, Globcover: a 300 M global land cover product for 2005 using ENVISAT MERIS time series, in: *The Proceedings of ISPRS Commission VII Mid-Term Symposium: Remote Sensing: From Pixels to Process*, Enschede, NL, May 8–11, 2006.
- [27] R.H. Weber, R. Weber, *Internet of Things*, Springer, New York, 2010.
- [28] D. Delyser, D. Sui, Crossing the qualitative-quantitative divide II: inventive approaches to big data, mobile methods, and rhythm analysis, *Prog. Hum. Geogr.* 37 (2) (2013) 293–305. <https://doi.org/10.1177/0309132512444063>.
- [29] G. King, Ensuring the data-rich future of the social sciences, *Science* 331 (2010) 719–721. <https://doi.org/10.1126/science.1197872>.
- [30] J. Georis-Creuseveau, C. Claramunt, F. Gourmelon, A modelling framework for the study of spatial data infrastructures applied to coastal management and planning, *Int. J. Geogr. Inf. Sci.* 31 (1) (2017) 122–138.
- [31] R.K. Barik, H. Dubey, K. Mankodiya, et al., GeoFog4Health: a fog-based SDI framework for geo-spatial health big data analysis, *J. Ambient Intell. Human Comput.* 10 (2019) 551–567. <https://doi.org/10.1007/s12652-018-0702-x>.
- [32] M.N. Kamel B, G. Peng, T. VoPham, An overview of GeoAI applications in health and healthcare, *Int. J. Health Geogr.* 18 (2019) 7. <https://doi.org/10.1186/s12942-019-0171-2>.
- [33] Z. Hu, Q. Ge, L. Jin, M. Xiong, Artificial Intelligence Forecasting of COVID-19 in China, arXiv, 2020 preprint arXiv:2002.07112.
- [34] B. Xu, B. Gutierrez, S. Mekaru, K. Sewalk, L. Goodwin, A. Loskill, E.L. Cohn, Y. Hswen, S.C. Hill, M. M. Cobo, A.E. Zarebski, S. Li, C.-H. Wu, E. Hulland, J.D. Morgan, L. Wang, K. O'Brien, S.V. Scarpino, J.S. Brownstein, et al., Epidemiological data from the COVID-19 outbreak, real-time case information, *Sci. Data* 7 (1) (2020) 106. <https://doi.org/10.1038/s41597-020-0448-0>.
- [35] CAICT: China Academy of Information and Communications Technology, Research Report on Data and Intelligent Application in Epidemic Prevention and Control (1.0), 2020. <http://www.caict.ac.cn/kxyj/qwfb/ztbg/202003/P020200305495005485729.pdf> 2020. http://www.caict.ac.cn/english/research/rs/202005/t20200511_281160.html (Accessed 7 May 2020 in English).
- [36] N. Grassly, C. Fraser, Mathematical models of infectious disease transmission, *Nat. Rev. Microbiol.* 6 (6) (2008) 477–487.
- [37] C. Zhou, F. Su, F. Harvey, J. Xu, *Spatial Data Handling in Big Data Era*, Springer, Beijing, 2016.
- [38] Health Commission of Hubei Province, 2020. http://wjw.hubei.gov.cn/bmdt/ztzl/fkxxgzbdgrfyyq/xxfb/202002/t20200213_2025580.shtml (Accessed 26 April 2020 in English).
- [39] S. Yuan, How China Is Using AI and Big Data to Fight the Coronavirus, 2020. <https://www.aljazeera.com/news/2020/03/china-ai-big-data-combat-coronavirus-outbreak-200301063901951.html>. (Accessed 10 May 2020).
- [40] WHO, SARS Outbreak Contained Worldwide, 2003. <https://www.who.int/mediacentre/news/releases/2003/pr56/en>. (Accessed 8 May 2020).
- [41] CECC, Central Epidemic Command Center, Press Release <https://www.cdc.gov.tw/En/Bulletin/Detail/pevkg6JalT40I4uB6wAWcg?typeid=158>, 2020. (Accessed 9 May 2020).
- [42] G. Lauren, Modelling the Spread of 2019-nCoV, John Hopkins Whitting School of Engineering, Center for Systems Science and Engineering, 2020. <https://systems.jhu.edu/research/public-health/ncov-model/>.

- [43] Y. Lee, Taiwan's New 'electronic Fence' for Quarantines Leads Wave of Virus Monitoring, 2020. <https://www.reuters.com/article/us-health-coronavirus-taiwan-surveillanc/taiwans-new-electronic-fence-for-quarantines-leads-wave-of-virus-monitoring-idUSKBN2170SK>. (Accessed 7 May 2020).
- [44] Geospatial – A Golden Thread in Fourth Industrial Revolution. <https://monde-geospatial.com/geospatial-a-golden-thread-in-fourth-industrial-revolution/>. (Accessed 8 May 2020).
- [45] O. Kurain, How the Indian State of Kerala Flattened the Coronavirus Curve the Guardian, 2020. <https://www.theguardian.com/commentisfree/2020/apr/21/kerala-indian-state-flattened-coronavirus-curve>. (Accessed 11 May 2020).