Chapter 8
Health-Based Geographic Information Systems for Mapping and Risk Modeling of Infectious Diseases and COVID-19 to Support Spatial Decision-Making

Xiao Huang, Renyi Zhang, Xiao Li, Bahar Dadashova, Lingli Zhu, Kai Zhang, Yu Li, and Bairong Shen

Abstract Infectious diseases remain an essential global challenge in public health. For instance, novel coronavirus (COVID-19) has resulted in significant negative impacts on public health, infecting more than 214 million people and causing 4.47 million deaths worldwide as of August 2021. Geographic Information Systems have played an essential role in managing, storing, analyzing, and mapping disease and related risk information. This article provides an overview of a broad topic on applications of GIS into infectious disease research. Our review follows the framework of human–environment interactions, focusing on the environmental and social factors that cause the disease outbreak and the role of humans in disease control, including public health policies and interventions such as social distancing/face covering practice and mobility modeling. The work identifies key spatial decision-making

X. Huang
Department of Geosciences, University of Arkansas, Fayetteville, AR, USA

R. Zhang
Department of Atmospheric Sciences, Texas A&M University, College Station, TX, USA

X. Li · B. Dadashova
Texas A&M Transportation Institute, Texas A&M University, College Station, TX, USA

L. Zhu
Department of Remote Sensing and Photogrammetry, National Land Survey of Finland, Helsinki, Finland

K. Zhang
Department of Environmental Health Sciences, University at Albany, State University of New York, Albany, NY, USA

Y. Li
School of Hydraulic Engineering, Dalian University of Technology, Dalian, China

B. Shen (✉)
Institutes for Systems Genetics, Frontiers Science Center for Disease-Related Molecular Network, West China Hospital, Sichuan University, Chengdu, Sichuan, China
e-mail: bairong.shen@scu.edu.cn

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issues where GIS becomes valued in the agenda for infectious disease research and highlights the importance of adopting science-based policies to protect the public during the current and future pandemics.

Keywords Infectious disease · COVID-19 · Geographic information system (GIS) · Social distancing · Spatial decision-making · Public health policy

8.1 Introduction

Environmental pollution, disasters, urbanization, global warming, and rapid population growth have become the significant factors that cause infectious disease outbreaks [1–3]. Infectious diseases remain an essential global challenge in public health, causing over 13 million deaths each year. According to statistics, viral hepatitis, influenza, and tuberculosis stand among the leading causes of illness and death in the United States [4]. Since 2019, novel coronavirus (COVID-19) started to be detected from humans, which rapidly developed into a global pandemic, infecting more than 214 million people, and causing 4.47 million deaths worldwide as of August 2021 [5]. COVID-19 has changed human production and life behavior not only affected the water system, but also had a strong impact on a wider range of energy systems and food systems under the global background of high coupling of food, energy, water, and environment, and then affects the process of sustainable development of economy, society, and environment in the whole region. For the energy system, the reduction of power demand and the decline of fossil fuel use caused by the economic recession during COVID-19 have significantly reduced the carbon dioxide emissions of the global power sectors [6–8].

The development of computer-based geographic information systems (GIS) for integrating and analyzing spatially referenced data has provided new tools for medical geographic research on infectious disease control. Infectious diseases have revealed strong spatial patterns, where Geographic Information Systems (GISs) played a central role in managing, storing, analyzing, and mapping disease information. The Coronavirus Resource Center established by the Johns Hopkins University is one of the noteworthy examples of this practice (see https://coronavirus.jhu.edu/map.html). Disease cartography began with Koch's work, including the spatial mapping of pandemics such as the European plague and yellow fever [9]. Later, the GIS-based disease mapping tools also leveraged many other kinds of data such as demographic, social media, and environmental data to improve disease surveillance and decision-making [10–12].

Spatial decision-making and spatial decision support systems have been widely discussed in the GIS research for solving real-world problems such as disaster management, environmental and water resources management, agriculture risk management, and public health surveillance [13–22]. The existing literature describing GIS-based public health applications suggests that GIS diffusion into infectious diseases research and public health practice has moved beyond the early innovation phase [23]. Such publications can be identified in an extensive range of outlets, including multidisciplinary journals on public health, environmental science, social science studies, GIS conference proceedings, and government reports. For instance, numerous COVID-19 related research articles have been published since 2019 in the journals (or proceedings) of environmental science, geography, geosciences, infectious diseases, computer science, and multidisciplinary studies. Nevertheless, it is unclear to what extent and depth GIS has been utilized in infectious disease studies. For instance, which types of infectious diseases research have attracted most GIS applications? What kinds of GIS-based methodologies have been used in analyzing infectious diseases? Some infectious diseases such as COVID-19 are highly contagious, where public health policies (e.g., social distancing), human behavior, and mobility analysis have been extensively analyzed with the help of GIS-based data and methodologies in infectious disease studies.

This review article tends to systematically review and inductively summarize the influential literature on applications of GIS into infectious disease research. Figure 8.1 illustrates the workflow of the article. Our review follows the framework of human–environment interactions, where the term "environment" represents the environmental and social factors that contribute to disease outbreak and transmission. The term "human" represents the role of humans in disease control, including public health policies and interventions such as social distancing practice and mobility modeling. This reminder of this review paper is structured into the following sections. Section 8.2 systemically reviewed and summarized the typical applications of four types of GIS techniques in infectious disease-related research, including spatial clustering and statistics, spatial interpolation, WebGIS and spatial visualization, and spatial modeling. In Sect. 8.3, we conducted an in-depth review of COVID-19 related research works. We paid particular attention to an emerging

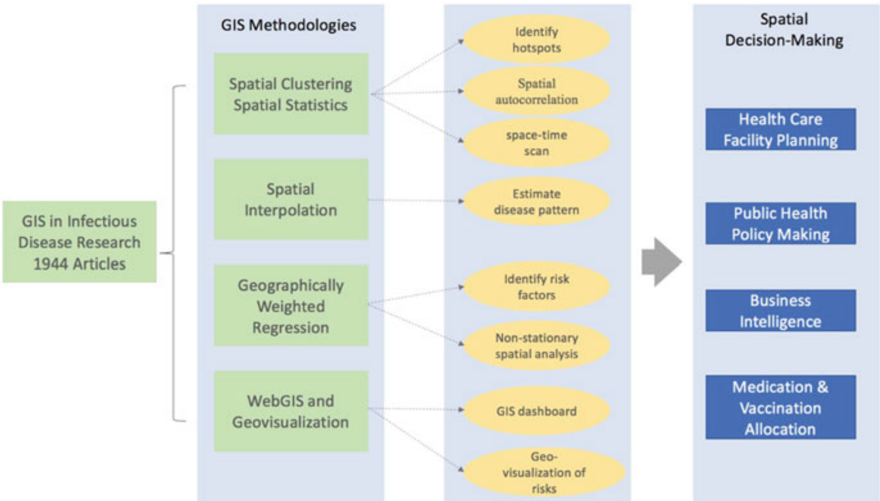

Fig. 8.1 Use of GIS in infectious disease research for spatial decision-making

geographic data source—fine-grained mobility data, reviewed, and summarized the existing efforts about how to use mobility data to assess different COVID-19 protective measures (e.g., social distancing) and how to use mobility data to facilitate decision-making during different stages of the pandemic.

8.2 Environmental Distribution of Infectious Disease and GIS-Related Research

This article first developed a search strategy with terms relating to "GIS/Geographic Information Systems" and "Infectious Disease." This search was developed through an iterative process of incorporating new terms and refining those included based on results returned and identification of relevant citations. We conducted an electronic search on the Web of Science database with no restriction on the date or language of publication. We found 1944 peer-reviewed articles that focus on infectious disease and involved GIS or spatial analysis. Figure 8.2 illustrates the number of identified articles by different publishers, with Springer Nature publishing the most GIS-related infectious disease research, followed by Elsevier and Willey.

In the next step, we used the keyword "GIS" combined with different types of infectious disease keywords such as "HIV," "Influenza," and "COVID-19" to group the articles by different disease types. Table 8.1 illustrates the number of articles (with their corresponding citations) that applied GIS and spatial analysis for each type of infectious disease. According to Table 8.1, Malaria, COVID-19, and Human Immunodeficiency Virus (HIV) are the top three diseases that mostly utilized GIS and spatial analysis in their relevant research works.

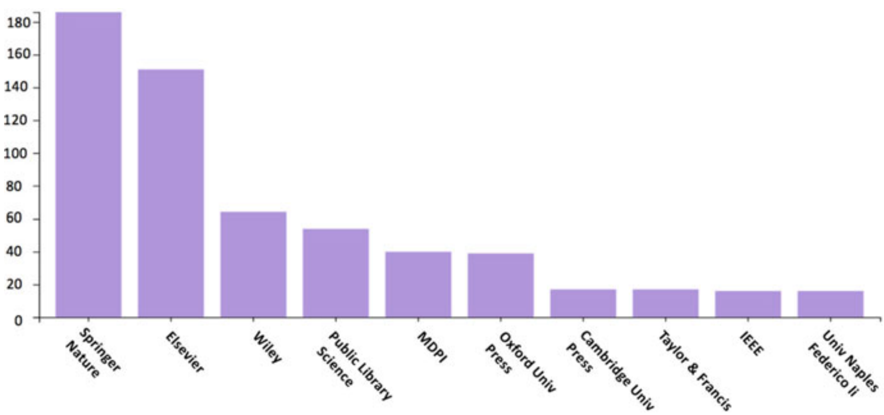

Fig. 8.2 Illustration of publishers for GIS-related infectious disease articles

Table 8.1 Illustration of several articles and citations that are related to applying GIS in infectious disease research

Infectious disease	Number of articles	Number of citations
Malaria	430	7233
COVID	226	1132
HIV/AIDS	212	2972
Escherichia Coli	193	3396
Tuberculosis	178	2299
Influenza	153	2213
West Nile virus	119	2153
Lyme	113	2554
Viral hepatitis	76	1202
Salmonella	57	1184
Severe acute respiratory syndrome	46	847
Pneumonia	36	716
Hand-foot-mouth disease	33	322
Measles	20	415
Meningitis	17	176
Whooping cough (pertussis)	11	139
Poliomyelitis	7	58
Diphtheria	6	561
Tetanus	5	75
Chickenpox	2	102
Giardiasis	1	12
Infectious mononucleosis	1	10
Mumps	2	11
Total	1944	39, 987

8.2.1 Use of Spatial Clustering and Spatial Statistics in Identifying Disease Hotspots

Spatial clustering and spatial statistics are two of the mostly used spatial analysis techniques for evaluating infectious diseases' geographic distribution (see Table 8.2). In this section, we searched for articles with keywords "infectious disease," "GIS," and "spatial clustering and statistics" in the Web of Science database. Results have returned with 49 articles. We removed duplicated and un-relevant articles and selected ten articles for analysis. Spatial clustering is used to partition spatial data (e.g., disease data) into a series of meaningful subclasses called spatial clusters, where spatial objects that are within the same cluster are similar to each other [36]. Spatial autocorrelation is often used in the GIS to identify how well objects correlate with other nearby objects across a spatial area [36]. As listed in Table 8.2, spatial autocorrelation was used in five articles for studying the spatial distribution of Hepatitis, Tuberculosis, HIV, Mumps, and SARS diseases. Spatial clustering methods such as Kulldorff's spatial scan and self-organizing maps were used in seven articles. In these articles, the spatial scan statistic identified statistically significant hotspots based on the number of disease cases by systematically scanning circular windows using varying sizes across the study area [26–28]. A space-time scan was used to test the statistically significant clusters of the disease cases across space and time [35]. Other spatial statistical models such as Local Moran's I are global clustering statistics that measure the tendency for points to occur closer together in space by chance across the entire study area [25, 31]. In contrast, the Kulldorff spatial scan statistic identifies local clusters in a particular region. Local clusters can exist in either the absence or presence of global clustering [26, 27].

8.2.2 Use of Spatial Interpolation in Estimating Disease Pattern

Another focused area of using GIS technology in infectious disease mapping is to create "heat maps' 'using data gathered in a limited number of locations to estimate values in unmeasured locations. Spatial interpolation is the process of using points with known values to estimate values at other points [36]. Traditional spatial interpolation methods include kriging interpolation, trend surface interpolation, and inverse distance weighted interpolation. As illustrated in Table 8.3, the kriging interpolation method has been used in six articles studying Burkholderia Pseudomallei, foot-and-mouth disease, norovirus, Tuberculosis, rotavirus, and influenza-like illness. Inverse distance weighted interpolation was used in four articles studying Malaria, Tuberculosis, Kala-azar disease, and Hepatitis. In these articles, spatial interpolation methods were often combined with spatial statistics to analyze spatial transmission patterns of infectious disease ([37, 40];). Spatial interpolation is often used to convert discrete data into continuous data for comparison with the spatial trend of infectious diseases [44, 45]. Others may consider spatial interpolation as a data processing method for spatial analysis [39, 40].

8.2.3 Spatial Visualization and Web-Based GIS Dashboard

With the advancement of web-based technologies (e.g., ArcGIS online), various web-based GIS platforms have been developed to visualize the infectious disease risks at different space-time scale. Some of the well-known dashboards include the WHO Coronavirus dashboard [46], John Hopkins University COVID-19 dashboard [47], the UK National Health Service (NHS) COVID-19 app [48], and CDC COVID-19 data tracker [5]. Spatial interpolation methods have often been combined with web-based geovisualization tools to predict the infectious disease spread patterns [37, 44, 45]. WebGIS and ESRI products such as ArcGIS dashboard are

Table 8.2 Selected studies using cluster detection and spatial statistics to characterize the spatial distribution of infectious disease

References	Study Country	Methods	Key findings
Stopka et al. [24]	United States	Hepatitis C virus/spatial autocorrelation Getis-Ord Gi* statistics	Largest clusters in Boston, New Bedford, Worcester, and Springfield HCV is positively associated with the race of the population
Rao et al. [25]	China	Tuberculosis Moran's I and spatial panel data model	The disease accidents are positively associated with temperature, precipitation, and wind speed
Gwitira et al. [26, 27]	Zimbabwe	HIV/AIDS and malaria Moran's I and space-time clustering Kulldorff's spatial scan	Identify risk areas based on clusters
Aturinde et al. [28]	Uganda	HIV-TB Moran's I and spatial scan statistics	Two clusters were identified in Lake Victoria and the presence of refugee camps
Yu et al. [29]	China	Mumps/spatial autocorrelation and Kulldorff space-time scan	Several clusters have been identified
Lai et al. [30] Lee and Wong [31]	Hongkong, China	SARS/spatial clustering, spatiotemporal clustering, global Moran's I	Origin-and-destination plots showed the directional bias and radius of the spread of superspreading events
Lantos et al. [32]	United States	Lyme/spatiotemporal cluster analysis	Northern Virginia experienced intensification and geographic expansion of Lyme disease cases.
Yang et al. [33]	Taiwan	HIV/spatial statistics	Spatial patterns of different HIV risk behaviors significantly differed in both local clustering patterns and global geographic distribution
Basara and Yuan [34]	United States	Infectious diseases/self-organizing maps	Identified positive relationship between environmental conditions and health outcomes in communities
Dong et al. [35]	China	Influenza (H7N9)/retrospective space-time permutation scan statistic	The epidemic moved from east to southeast coast, and hence to some central regions of China

Table 8.3 Use of spatial interpolation in infectious disease research

Reference	Country	Methods	Key findings
Saengnill et al. [37]	Thailand	Burkholderia Pseudomallei/Mann–Whitney U test, chi test, semivariogram model, and indicator kriging	Burkholderia Pseudomallei is not significantly associated with spatial soil factors. The lag distance between positive case is 90.51 m
Perez [38]	Pakistan	Foot-and-mouth disease/probability co-kriging	A higher risk of disease is associated with increased contact with infectious animal migration
Siya et al. [39]	Uganda	Malaria/inverse distance weighted interpolation (IDW) and Mann-Kendall trend test	Malaria is declining during the study period; rainfall plays an important role in malaria burdens. Altitudes can affect the key factors
Bhunia et al. [40]	India	Kala-azar disease/IDW, Moran index, Getis-Ord Gi*	Southeastern and northwestern part of the study area are with higher incidence rate; Kala-azar incidences are positively correlated for five consecutive years; the spatial trend of disease diffusion is shown
Liu et al. [41]	China	Hepatitis E/trend surface, IDW, spatial-temporal analysis	Higher incidences in northwestern counties of the study area; suggest the need for strengthened supervision and surveillance of sanitary water, sewage treatment, and food in high-risk areas
Inaida et al. [42]	Japan	Norovirus/kriging	Incidences increase in southern areas at first and extend to northern areas in Japan
Ding et al. [43]	China	Multidrug-resistant tuberculosis/kriging	The proportion of MDR-TB cases in all TB cases are higher during 2006–2009 and lower during 2010–2012
Török et al. [44]	USA	Rotavirus/kriging	Confirm the trends of rotavirus activity and identify the variability in the timing of peak disease activity
Sakai et al. [45]	Japan	Influenza-like illness/kriging	Two spreading patterns are observed

commonly used technology for geographical data sharing, visualizing [49]. WebGIS techniques were used in three articles for establishing visualization platforms [50, 51]. Google Maps were used in two articles for visualizing infectious disease information [50, 51]. As one of the most representative WebGIS platforms, ArcGIS Online provides various mapping and analysis functions, geographic data sources, and web-based applications, allowing users to effectively build up web applications

Table 8.4 Use of WebGIS techniques and geovisualization in infectious disease monitoring

Reference	Country	Methods	Key findings
Lu [52]	China	Infectious disease in general/WebGIS, J2EE based architecture is applied to construct a distrusted system infrastructure	A platform that contains georeferenced data can convert disease information into graphical and visual form
AI Manir et al. [53]	Global	Malaria/dashboard	Prototype of surveillance platform for accessing distributed disease data sources
Li et al. [50]	China	Infectious disease in general/WebGIS, Google maps	The platform can display infectious disease emergencies information and transfer information between workers in the field and decision-makers through the internet
Yang et al. [51]	China	Schistosomiasis/Google earth, WebGIS	A WebGIS platform that can operate search, evaluation, risk analysis and prediction. This platform can help identify early high-risk areas and provide detailed information
Patrick et al. [54]	USA	HIV/calculate the proportion of ever tested, tested positive and newly positive in the past year; chi-square test for trend	This dashboard can be used to complement the HIV care continuum
	USA	COVID-19/dashboard	An online dashboard that can display COVID-19 data for every county of 188 metropolitan areas in the USA
Cheng et al. [55]	China	Influenza/dashboard	An influenza surveillance dashboard with several data streams and indicators for monitoring disease activities
Ravinder et al. [56]	India	COVID-19/dashboard	A web-based dashboard that provides a 3-week prediction of COVID-19 incidences

without coding. Meanwhile, it also provides different GIS tools and APIs used by developers while it is not as functional as ArcGIS Desktop. The Google Maps API provides embedded Google Maps into web pages through JavaScript. The APIs provide many utilities to generate maps and customize the map content by adding additional information services. However, these APIs do not support complicated analysis functions. Table 8.4 illustrates selected articles that have used WebGIS techniques and geovisualization in infectious disease monitoring.

8.2.4 *Exploring Environmental and Social Factors Using Spatial Regression Analysis*

Several articles are focused on investigating the key factors that affect the occurrence and spread of infectious diseases. Geographically Weighted Regression (GWR) has a high utility in epidemiology, particularly for examining the relationship between the spread of infectious disease with different social, political, and environmental factors (e.g., built environment, health policies, and interventions). GWR is a local form of linear regression used to model spatially varying relationships [57]. Table 8.5 illustrates the key social and environmental factors that have been explored in infectious disease research. According to Table 8.5, environmental factors such as temperature, humidity, precipitation, wind speed, air pressure, altitude, and socioeconomic factors such as child population density and per capita Gross Domestic Product (GDP) are associated with Hand, Foot, and Mouth Disease (HFMD). Other environmental factors such as air pollution, brickfield density, land use, and public transportation facilities significantly impact on COVID-19 cases. Other sociodemographic factors such as gender, nationality, employment status, and occupation types are associated with malaria and tuberculosis.

8.3 Human-Centered Efforts to Address COVID-19 Challenges

Novel coronavirus (COVID-19) has significant negative impacts on public health, infecting more than 214 million people and causing 4.47 million deaths worldwide as of August 2021. The COVID-19 pandemic is much more pronounced than many of the previous outbreaks of infectious diseases, including the 2002/2003 SARS. The enormous scope and magnitude of the COVID-19 outbreak reflects a highly contagious nature and exceedingly efficient transmission for SARS-CoV-2. There exists two primary pathways for respiratory viruses to be transmitted from person to person (Fig. 8.3a). Virus-bearing particles are produced from breathing, talking, coughing, or sneezing by an infected person. Interhuman transmission occurs by the direct (deposited on persons) or indirect (deposited on objects) contact route via respiratory droplets (>5 μm) or the airborne route via respiratory aerosols (<5 μm). While large respiratory droplets readily settle out of air to cause person/object contamination, small virial-bearing respiratory aerosols are efficiently dispersed in air and inhaled by human to lead direct deposition along the respiratory tract and to cause infection [13, 14, 19]. Well-established public health measures to prevent interhuman transmission include face covering, social distancing, and testing/quarantine (Fig. 8.3b). There exists now compelling scientific evidence for the importance of airborne transmission in spreading the COVID-19 disease and face covering in preventing interhuman [11, 13, 14, 19]. Also, increasing ventilation in an enclosed community setting has been shown to effectively reduce viral

Table 8.5 Exploring environmental and social factors that cause infectious disease

References	Infectious disease/environmental factors	Methods	Key findings
Hassan et al. [2]	COVID-19/$PM_{2.5}$ pollution, population density, brickfield density, rainfall, wind speed, poverty level	GWR	Significant robust relationships between these factors were found in the middle and southern parts of the city, where the reported COVID-19 infection case was also higher
Wu and Zhang [58]	COVID-19/social, economic, and environmental factors such as population density, hospitalization, and age	GWR and principal component analysis (PCA)	In El Paso, Odessa, Midland, Randall, and Potter County areas in Texas, population, hospitalization, and age structures are presented as static, positive influences on COVID-19 cumulative cases
Ge et al. [1]	Hemorrhagic fever with renal syndrome (HFRS)/temperature, average humidity, average rainfall, area, rodent density, human population density, water area, and surface mean elevation	Seasonal difference-geographically and temporally weighted regression	Meteorological factors notably impacted the changing trends of HFRS outbreaks
Sun et al. [3] Hong et al. [59] Hu et al. [60] Dong et al. [61] Hu et al. [62]	Hand, foot, and mouth disease (HFMD)/temperature, humidity, precipitation, wind speed, air pressure, altitude, child population density, and per capita GDP	GWR, geographically and temporally weighted regression	The findings help to understand the seasonally and spatially relevant effects of natural environmental and socioeconomic factors on the HFMD
Yang et al. [63]	Malaria/occupation, annual average temperature, annual cumulative rainfall, rice yield per square kilometer and proportion of rural employees	GWR	Temperature, precipitation, rice cultivation, and proportion of rural employees were positively associated with malaria incidence

(continued)

Table 8.6 (continued)

References	Infectious disease/environmental factors	Methods	Key findings
Lak et al. [64]	COVID-19/12 quantitative place-based variables related to physical attributes, land use and public transportation facilities, and demographic status	GWR	Demographic composition and major neighborhood-level physical attributes are important factors explaining high rates of infection and mortality
Mohidem et al. [65]	Tuberculosis (TB)/gender, nationality, employment status, health care worker status, income status, residency, smoking status as well as; environmental factors such as AQI, CO, NO_2, SO_2, PM10, rainfall, relative humidity, temperature, wind speed, and atmospheric pressure	Moran's I, Getis-Ord Gi* statistics Geographically weighted regression	Sociodemographic factors were associated with TB cases ($p < 0.05$). GWR model was the best model to determine the spatial distribution of TB cases

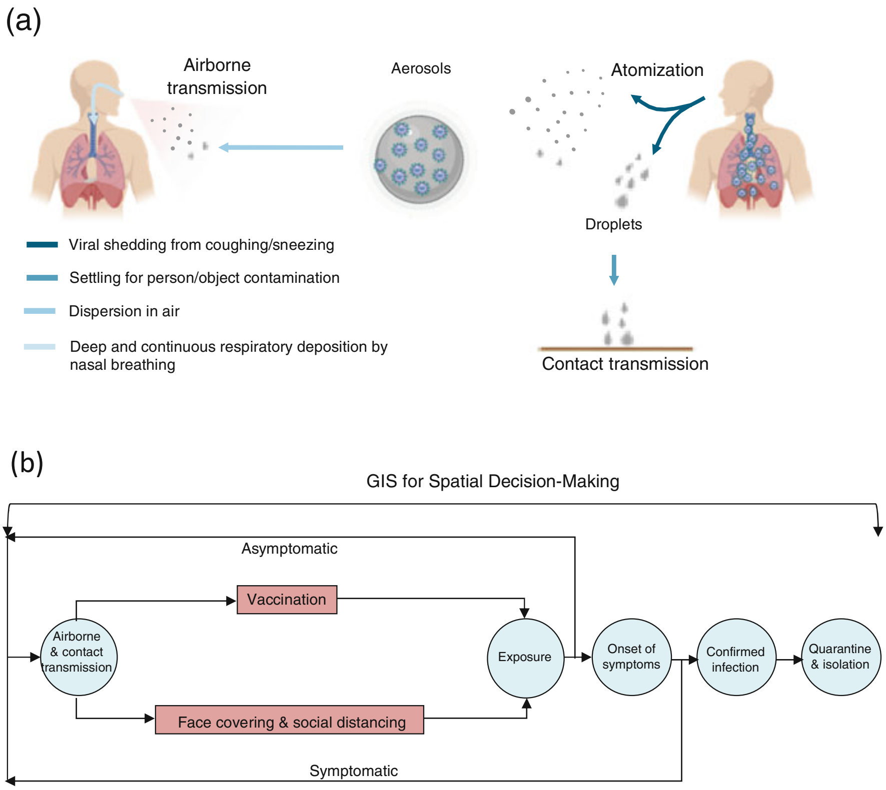

Fig. 8.3 Transmission, science-based intervention, and application of GIS. (**a**) Illustration of viral transmission routes (adopted from Zhang et al. 2020). (**b**) Mitigation for preventing interhuman transmission and the application of GIS in decision-making. The boxes denote mitigation measures, and the circles depict the disease evolution

transmission [66]. Vaccination is commonly believed to mitigate viral transmission, albeit for the occurrence of break-through infections [67]. The effectiveness of vaccination has been clearly documented to significantly reduce hospitalization, severe syndromes, and mortality [68].

As the COVID-19 outbreak grew to an epidemic, and various GIS systems have been developed and implemented, leading the response to COVID-19 in many ways. For instance, Johns Hopkins University launched its COVID-19 dashboard using ESRI technology [47]. So far, social distancing plays an important role in controlling the spread of coronavirus. Governments issued different level of restrictions on traveling, institutions canceled gatherings, and citizens socially distanced themselves to limit the spread of the virus. Social distancing measures have significantly influenced the mobility patterns, which have been widely discussed in various COVID-19 related GIS applications. On the other hand, those literature are also tightly related to public health policy and social equity issues, which are worthy of future research. This article illustrates the key findings of using GIS in mobility and policy analysis during the COVID-19 pandemic. We structured our reviews by different stages of pandemic control, i.e., early stage, controlling stage, reopening stage, and post-pandemic recovering stage. We found 228 articles related to the topic. In the following four subsections, we discuss human-centered efforts that leverage mobility data in addressing COVID-19-related challenges.

8.3.1 Early in the Pandemic: Contact Tracing and Initial Control

At the early stage of the COVID-19 pandemic, location-based intelligence has been widely adopted to provide situational awareness for policy-makers and researchers. Human mobility records retrieved from cell phone users' location data (by way of GPS, cell phone towers, and/or Wi-Fi), electronic wristbands, credit card transactions, and closed-circuit television (CCTV) systems can assist in tracking disease spread and enforcing social isolation measures [69]. In China, Alipay and WeChat, two big providers of mobile payment systems, released apps that combine users' health, location, and financial data to generate a personal infection risk rating [70]. Other government-backed apps were also used in the early stage of the pandemic to collect users' essential information, and necessary user scanning was required at checkpoints to better gauge people's moving patterns. Besides efforts and guidelines by the officials, crowdsourcing efforts are also popular, as citizens themselves can contribute to contact tracing and surveillance by voluntarily sharing their whereabouts online. For instance, Private Kit (https://privatekit.mit.edu/), released by the Massachusetts Institute of Technology, is a crowdsourcing application that stores GPS location records from users every 5 min for up to 28 days. Users have the option to share their location data and notify health officials if they test positive for COVID-19. Numerous studies have proved that human mobility records with fine spatiotemporal granularity are essential for disease spread control, as reconstructed trajectories of individuals who have been tested positive can be used to alert those who may have been put at risk of infection [71, 72]. Zhang et al. [13, 14, 19] studied the relationship between human mobility and the cross-space infection in the early stage of the pandemic, based on which a variety of counterfactual analyses is developed to examine the necessity of lock-down and the other containment approaches.

8.3.2 During Control Measures: Compliance Monitoring

To contain the COVID-19 pandemic, one of the non-pharmacological epidemic control measures is to reduce the transmission rate of SARS-COV-2 in the population via social distancing or other similar quarantine measures [11, 73]. Besides the proof from epidemiologic simulations, many pieces of evidence have been found in numerous studies that the implementation of mobility-restricting measures is responsible for the declined transmission rates (e.g., [74, 75]). In certain cases, however, different countries, states/provinces, counties/towns, and other administrative units choose to handle COVID-19 in different ways, with great disparity in the implementation of policies and guidelines. Even in regions under the same level of restrictions, disparities in compliance tend to occur. Human mobility records, either at the individual level or aggregated to certain geographic units, can reflect how people adjust their travel patterns under the COVID-19 pandemic and whether policies are implemented in an effective manner. There are some notable efforts that Huang et al. [76] analyzed over 580 million tweets worldwide to investigate how people follow mobility-restricting measures at the global, country, and U.S. state levels. Their results revealed great discrepancies in responsiveness, evidenced by the contrasting mobility patterns in different epidemic phases at their investigated scales. Taking advantage of Google's COVID-19 mobility reports, Bargain and Aminjonov [77] investigated how policy compliance is linked with political trust at the regional level in Europe. Their findings indicate that high-trust regions decrease their mobility significantly more than low-trust regions, and the efficiency of policy stringency in terms of mobility reduction significantly increases with trust. Other efforts coupled mobility-related indices with sociodemographic factors, aiming to reveal the determinants that potentially lead to the disparity in policy compliance (e.g., [78]; Chiou and Tucker). The general findings point to the luxury nature of mobility-restricting measures (e.g., working from home and other virtual working conditions) with which socioeconomically disadvantaged groups cannot afford to comply. Zhu et al. [79] utilized network optimization to identify how the geographical centers of the pandemic moved spatially over time across the USA in the context of various intervention policies. The pandemic has also witnessed much mis- and dis-information. Network reconstruction methods can be employed to measure the interaction between the information diffusion and the outbreak of COVID-19 across space, and identify both positive and negative impact of information on the pandemic [12, 15]. The above evidence reveals the essential role of mobility data in policy compliance monitoring during the COVID-19 pandemic, which benefits further policymaking in terms of adjusting controlling measures and mitigating compliance disparity.

8.3.3 Reopening: When, How, and Where

After the implementation of mobility-restricting measures, federal and local government officials have been investigating reopening strategies, such as when and where to reopen borders and business, and how much activities are allowed in certain places. These reopening strategies, however, should be determined in a scientific manner with the assistance of epidemiological models that consider human mobility dynamics. Many studies have been conducted to assist in reopening decision-making taking advantage of fine-grained human mobility data. One notable effort is by Chang et al. [80], who built enormous mobility networks containing 5.4 billion hourly edges from mobile phone data that cover hourly movements of 98 million people from 56,945 U.S. census block groups to 552,758 points of interest (POIs). The results suggested that, coupled with detailed mobility records, their simulation can estimate the effects of specific reopening strategies in the USA. Using the same dataset, Andersen et al. [81] examined U.S. college reopenings' association with changes in human mobility within campuses and in COVID-19 incidence in the U.S. counties of the campuses over a 10-week period around college reopenings. They found that college reopenings were associated with increased campus mobility, responsible for the increased COVID-19 incidence by 2.7 cases per 100,000. Xiong et al. [82] investigated the partial reopening phases in the USA by leveraging anonymized mobile device location data from over 100 million monthly active users procured from multiple third-party data providers. The detailed mobility records coupled with their models revealed the high likelihood of a second spike in coronavirus in many early-opening regions. The above examples highlight the necessity of human mobility data in optimizing reopening decisions.

8.3.4 Post-Pandemic: Recovery and Transition Gauging

Human mobility data can be used to tell stories regarding how different regions recover after the lifting of strict mobility-restricting orders and the implementation of reopening policies by comparing the human moving patterns in post-pandemic situations to the ones in pre-pandemic situations. While some of the changes are temporary, such as the disruptive social, physical, and economic activities in urban and rural landscapes during the stay-at-home orders (most of which have largely recovered after the reopening), others seem to be permanent impacts that force multiperspective transitions in an irreversible manner. Human mobility data that cover multiple stages are expected to benefit the investigation of the dynamic, intertwining, long-term societal effects of the COVID-19 pandemic, filling the knowledge gaps in our understanding of how spatial and social interactions have shifted and transitioned in the post-pandemic world, and informing better adapting, responding, and recovering strategies that reduce inequalities and vulnerabilities. Despite the fact that it is difficult to decide when the post-pandemic era really starts, numerous efforts have been made to gauge recovery and transition when society functions resume. Kupfer et al. [83] investigated park visitation recovery by mapping and analyzing the spatiotemporal patterns of visitation for six national parks in the western USA, taking advantage of large mobility records sampled from mobile devices and released by SafeGraph as part of their Social Distancing Metric dataset. Huang et al. [78] leveraged multi-source mobility datasets from Google, Apple, Descartes Labs, and Twitter to investigate how people reduced their travels during the mobility-restricting period and how mobility recovered after the reopening at the county level in the USA. Their results revealed a great disparity in mobility dynamics in the recovery phase, as the poor countries tended to gain earlier and greater upward momentum than the wealthy counties. Such disparity in recovery has been noted by many studies that take advantage of mobility records (e.g., [76, 83]).

8.4 Conclusion and Discussion

Adopting science-based policies are paramount in protecting the public during the current and future pandemics. This article provides an overview and a summary on applying applications of GIS into infectious disease research, and application of GIS tools for analyzing and maintaining COVID-19. We paid special attention to COVID-19 related research in terms of human-environment interactions. The term “human” represents the role of humans in disease control, including public health policies such as social distancing practice and mobility modeling. A total of 1944 peer-reviewed GIS-based infectious disease research articles were identified, where Springer Nature published the most articles, followed by Elsevier and Willey. Spatial analysis methods such as spatial clustering, spatial statistics, and spatial interpolation (e.g., Kriging), and GWR analysis have been discussed in detail in those articles to demonstrate the important value of using GIS and spatial analysis in infectious disease monitoring. The article also provides the summary of web-based portals (e.g., GIS dashboards) in visualizing infectious disease risks.

The article also includes a review on human-centered methods for COVID-19 research, including the analysis of social distancing and mobility in COVID-19 disease control and policymaking. We structured this section by different pandemic stages, including early-pandemic, under strong control measures, reopening, and post-pandemic recovery. In the early stage, several articles discussed using human mobility records derived from emerging geo-data sources (e.g., cell phone location data, electronic wristbands, credit card transactions, and closed-circuit television (CCTV) to assist in tracking disease spread and enforcing social isolation measures. In the disease controlling stage, much evidence has been found that the implementation of mobility-restricting measures is responsible for the declined transmission rates. Later in the reopening and recovery stages, human mobility data has demonstrated effectiveness in determining how different regions recover after lifting social distancing orders by comparing the human moving patterns in post-pandemic situations to those in pre-pandemic situations.

According to the literature review performed in this study, GIS has been frequently used to prevent and control of infectious diseases to facilitate the appropriate spatial decision-making. By identifying spatial hot spots/patterns and potential risk factors of infectious diseases as well as vulnerable populations, the governmental and public health agencies, health care organizations, and other stakeholders, can put more efforts and resources into those regions and develop effective prevention strategies and mitigation actions. Furthermore, spatiotemporal disease modeling (e.g., Geographically and Temporally Weighted Regression) could also advance the understanding of spatiotemporal variation characteristics of the environmental and sociodemographic factors on the disease incidence and prevalence. Leveraging GIS techniques in COVID-19 research may produce broad impacts in spatial decision-making such as health care facility planning, public health policymaking, business intelligence, and health equity solutions.

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