20 Applications of Geographic Information Science and Technology to Monitor and Manage the COVID-19 Pandemic

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Abstract

Computerized Geographic Information Systems (GIS) have been in use since the 1960s, but recently the rapid spread of the highly contagious COVID-19 disease, caused by SARS-CoV-2 virus, has led to unprecedented interest in and reliance on geospatial data and visualizations to help monitor and manage the resultant pandemic. Geospatial factors such as human proximity, movement, and interaction play a central role in this pandemic, and the widespread availability of geospatial data from remote sensing and Global Positioning System technologies are fostering GIS analyses and dashboards that communicate information about its spread. Advances in computing technology are now capable of supporting near-real-time visualization of COVID-19 cases where space–time analysis and GIS software limitations were formerly a bottleneck for epidemiological studies. This chapter describes the current status of the COVID-19 pandemic and defines GIS terms that should be considered when reviewing COVID-19 geospatial analysis as many maps have been created hastily. Examples are provided of near-real-time surveillance websites, and other spatial analyses that show the

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impact of COVID-19 lockdowns on the environment, including effects on wildlife, air pollution, noise pollution, and water turbidity. Wastewater-based epidemiology is discussed as traces of virus components in sewage can also be used to monitor COVID-19 cases. Finally, new and emerging technologies such as contact tracing applications using mobile technology, as well as drones, and robots that reduce human exposure to the virus are discussed as applied to the pandemic. Recommendations are made for improving GIS applications for future pandemics.

Keywords

Coronavirus · COVID-19 · Drone · Environment · GIS—Geographic Information Systems · Health · Lockdown · Pandemic · Pollution · Robot · SARS-CoV-2 · Spatial analysis Technology · Virus

20.1 Introduction

A new virus, SARS-CoV-2, the causative agent of COVID-19, suddenly emerged late in 2019 and quickly spread around the world, causing hundreds of thousands of deaths. By March 2020, the World Health Organization (WHO) declared it a pandemic, with the United States regularly appearing on the list of countries with the highest number of confirmed cases (WHO; https://apps.who.int/iris/handle/10665/332196). As a result, many predictive disease forecasting models, near-real-time surveillance websites, contact tracing applications (apps) (computer applications downloaded to mobile devices), and other spatial analyses using Geographic Information Systems (GIS) have been created at an explosive rate to help monitor and manage this pandemic.

Computerized GIS platforms have been available since the 1960s and have previously been applied to epidemiological studies with some software and technological limitations (Ahasan et al. 2020). However, only recently, in alignment with the COVID-19 outbreak, has the technology improved to where geospatial methods are now widely accessible and readily being used, especially on mobile technology, providing informative results (Nguyen et al. 2020). Many health-based apps have emerged in the last several years with the proliferation of smartphones around the world and greater access to geospatial data (Gupta 2013; Carrion et al. 2016). These apps have provided a user-friendly framework to collect and share information about the spread of COVID-19. GIS provides many tools to create maps and other analyses often derived from remote sensing and Global Positioning System (GPS) technologies. Such tools provide statistics about disease propagation, give predictions about future outbreaks, and track changes in human movements and behavior. Many online near-real-time dashboards have been quickly created utilizing these tools; several provide information about spatiotemporal patterns of the pandemic and are useful for predictive modeling to manage outbreaks (Franch-Pardo et al. 2020). These have helped guide healthcare professionals and government officials in making virus-planning decisions, in addition to becoming extremely popular to citizen-scientists who monitor the intensity of an outbreak in their communities.

Medical geography and epidemiological surveillance have historically been used to manage diseases like the plague and Ebola (Koch 2016). Currently existing surveillance tools now provide a backbone to inform healthcare professionals and the public about virus movement and infection (Emch et al. 2017). Healthcare workers can use geospatial analyses to evaluate spatiotemporal patterns of a virus outbreak and create predictive models enabling appropriate management decisions (Franch-Pardo et al. 2020). Little was initially known about COVID-19, and as new information was found and theories changed, misinformation spread both on social media and amongst healthcare professionals and government officials. Many governments are quickly developing online dashboards that can provide COVID-19 statistics in near-real-time, including number of cases, deaths, and recoveries within their region and battle the spread of misinformation. As many citizens have had to restrict their normal day-to-day activities during mandated lockdowns, dashboards have become popular to help determine changing movement patterns and activities.

GIS systems and GPS data are more valuable and important now that mobile technologies and smartphones have begun to proliferate. With the increasing Internet speeds of mobile devices, users can access large datasets quickly, which is critical to monitor this pandemic in 2020 (Ienca and Vayena 2020). Contact tracing apps have been developed to track the movements of people through GPS technology in smart watches, smart phones, and even vehicles; this can help determine if one person encountered another person infected with SARS-CoV-2. One of the current limitations to contact tracing apps are privacy concerns raised from the processes by which large corporations, or government entities, may obtain detailed location or identity information of smart technology users (Ienca and Vayena 2020). New solutions for contact tracing can use wireless interfacing technology (WiFi) in combination with sound sensors on a smartphone to estimate distance by sound, which has fewer false positives than when just Bluetooth, the latest iteration of which is Bluetooth low energy (BLE), is used (Nguyen et al. 2020). WiFi and sound can be used together, or BLE can be used as good intermediaries between privacy and the need for accurate contact tracing without using the GPS sensor on a phone (Nguyen et al. 2020).

Studies have expressed concerns about the limited utilization of GIS and accuracy of the analyses that have been created to visualize the spatial spread of the outbreak; they have reported limitations in sharing real- or near-real-time spatial data between governmental agencies and more diverse enterprises (Ahasan et al. 2020; Field 2020; Franch-Pardo et al. 2020; Smith and Mennis 2020; Zhou et al. 2020). Ahasan et al. (2020) reviewed over 79 different articles that used GIS or geospatial tools for their analysis, of these only nine articles focused on the spatial patterns of COVID-19 disease spread, whereas 25 articles used GIS to focus on environment-related issues to COVID-19. One review of 63 studies criticized many of the online dashboards as overly complex, hard to understand, and slow to load the contents (Franch-Pardo et al. 2020). Nevertheless, there have been many positive aspects and incredible technological developments to the explosive production of GIS analyses for the pandemic.

By 2020, limitations previously considered as bottlenecks for epidemiological analyses were largely eliminated through technological advances. Potential to rapidly obtain considerable information about COVID-19 now is widely available for the public and healthcare professionals, especially with the production of near-real-time online COVID-19 dashboards (Ahasan et al. 2020). This chapter provides a brief description of the COVID-19 pandemic and relevant GIS and GPS technology, and provides examples of GIS applications and technologies used to monitor and manage the pandemic. Examples of specific environmental applications will be given, such as the use of GIS for development of information about changes in movement patterns and behaviors of humans and wildlife during the COVID-19 lockdowns. Future recommendations will be given for improved application of GIS to epidemiological spatial analysis and local monitoring of disease magnitude and rate of spread.

20.2 Description of the Global COVID-19 Pandemic

A novel coronavirus was first discovered in December 2019 when an outbreak of pneumonia-like symptoms, a disease of unknown origin, appeared in Wuhan City, Hubei Province, China (WHO; https://www.who.int/news/item/27-04-2020-who-timeline%2D%2D-covid-19). The disease was linked to persons who had been exposed to the virus at the Seafood Wholesale Market of Huanan in the city. This is a wet market where wild animals are sold and used as food. Scientists are still debating on how the virus originated. However, based on genetic codon usage studies and sequencing data, many experts believe it may have originated from animal hosts (zoonotic origin), such as bats or pangolins, followed by human-to-human transmission. The causative virus was initially called "novel coronavirus 2019" (2019-nCoV) by WHO. Later genome sequencing analysis revealed that the novel virus has a close relation with another coronavirus SARS-CoV (severe acute respiratory syndrome coronavirus), therefore it was renamed as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) by the international committee of the Coronavirus Study Group (CSG). Since the novel coronavirus spread so quickly around the world and resulted in thousands of deaths, WHO declared it a pandemic on March 12, 2020. WHO named the disease "COVID-19" for the coronavirus disease of 2019 and named the virus "Severe acute respiratory syndrome coronavirus 2" or SARS-CoV-2. As of October 14, 2021, there have been a total of 240,023,070 worldwide COVID-19 cases and 4,891,303 COVID-19 deaths (Worldometers, https://www.worldometers.info/coronavirus/).

Coronaviruses (CoV) are a group of enveloped positive-stranded RNA virus genera, having divergent evolution in relation to their receptor binding S1 subunit of their spike protein (Li 2012). Sequence analyses have shown that SARS-CoV-2 is closely related to SARS-CoV that emerged in 2002–2003 and the Middle East respiratory syndrome coronavirus (MERS-CoV) that emerged in 2012. Original

SARS-CoV-2 has mutated into several variants, including the D614G strain that has increased its infectivity (Korber et al. 2020).

SARS-CoV-2 is highly contagious and results in a mild, moderate, or severe illness and possibly even death. It can spread through close physical contact (usually within 6 ft.) between two people when one has the virus. The respiratory droplets (containing the virus particles) are released from an infected person who is sneezing, coughing, yelling, singing, talking, or just breathing, and they land on the eyes or are inhaled into the body through the nose or the mouth. The tiny droplets can linger for a long time in the air and sometimes they travel further than 6 ft., which facilitates airborne transmission of this disease (Prather et al. 2020). According to the U.-S. Centers for Disease Control and Prevention (CDC), COVID-19 is less likely to spread through contact with contaminated surfaces, although SARS-CoV-2 can survive on surfaces for hours or days. For example, it can survive on copper for 4 h, paper for 1 day, and plastic for 3 days (van Doremalen et al. 2020). Animals that can be infected with SARS-CoV-2 are reported to include cats, dogs, tigers, gorillas and minks. Humans have contracted COVID-19 from animals, such as on mink farms (Oude Munnink et al. 2021). Persons have the highest risk of contracting COVID-19 if they stay indoors with no ventilation or if they are in big crowds and do not follow social distancing guidelines such as wearing a mask.

The CDC has listed COVID-19 symptoms as (1) fever or chills, (2) cough, (3) shortness of breath or difficulty breathing, (4) fatigue, (5) muscle or body aches, (6) headache, (7) recent loss of taste or smell, (8) sore throat, (9) congestion or runny nose, (10) nausea or vomiting, and (11) diarrhea (CDC; https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html). However, up to 40% of individuals can be asymptomatic depending on how long it has been since their initial exposure to the virus, their age, and other factors (CDC; https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html).

There are two types of diagnostic tests commonly available for COVID-19, a viral antigen test and an antibody test. For the viral antigen test, a RT-qPCR-based method where specimens can be obtained through an anterior nasal swab or saliva is most frequently used. The nasal swab method can put healthcare workers at risk as they must insert a swab into the patient's nose. Specimens also can be collected at home using an at-home-testing kit, which are then processed by a lab or sent to a testing center. RT-qPCR testing usually requires an expensive RT-PCR machine. Analysis of the sample is time-consuming and expensive as chemicals are used. Quicker, less expensive tests are now available, such as for the viral antigen. For example, the US company, Abbott, developed the BinaxNOW™ COVID-19 Ag Card. The test results can be obtained in 15 min and cost only $5 (Abbott; https://www.abbott.com/BinaxNOW-Test-NAVICA-App.html#/). So far, there are no commonly available potent antiviral drugs (including engineered antibody drugs) or vaccines to treat or prevent COVID-19. Lockdowns, wearing masks, social distancing (e.g., 6-ft. apart), and frequent hand washing with soaps are some of the important strategies currently used to reduce the spread of the virus. The lockdowns have had a huge impact on human movements and activities; as workers transitioned to work at home, in-person learning was canceled at schools, and shopping and recreational activities were constrained. As movement patterns changed, GIS began to be used to study the impact. It was observed that movement patterns changed considerably during the lockdown, with both positive and negative impacts on the environment (Teixeira and Lopes 2020; Road Ecology Center 2020).

20.3 Geographic Information Science and Global Positioning System

Goodchild and Longley (1999) said "the computer is no longer part of the research environment—we are rapidly approaching a world in which the computer is the research environment." Geographic information science is an important example of how this process has been transformative as most current GIS systems are now computer-based. GIS uses geospatial data to analyze different geographic or spatial patterns of movement or occurrences of phenomena under study (Maguire 1991). Many different fields of geographic research and analysis use these computer-based systems, or manual systems, as a tool (Maguire 1991). For these reasons, GIS may be considered as a "background technology (more akin to word-processing than, say, spatial interaction modeling)" (Maguire 1991; Goodchild and Longley 1999).

GPS, originally developed by the US military, is a satellite-based global navigation system that can provide coordinates for geographical locations on the Earth (Krenn et al. 2011). Maps are often created by gathering spatial data from GPS technology that generates coordinates for a given location. Mobile GPS units are now widely available, such as those developed by Garmin. Cell phones have built-in GPS, and many cars even have navigation systems that use GPS to show locations mapped on a visual display. With the rise of smartphone technologies, advanced smartphone sensors, and BLE, contact tracing with cellphone use is becoming a more powerful tool for healthcare professionals in pandemics (Nguyen et al. 2020).

GIS includes spatial statistics, visualization, and creation of maps that can utilize remotely sensed imagery (Smith and Mennis 2020), such as those displayed by Google Earth (https://www.google.com/earth/). The Google Earth app has simplified access to GPS coordinates and enabled the general public to add their own coordinates derived from separate mobile GPS units. All of this can be done with very little knowledge and experience about GIS or GPS systems. Environmental Systems Research Institute (ESRI) Inc. (Redlands, CA), the developer of one of the most popular GIS software platforms, has also created online versions for the general public to create online maps. Improved GIS software and increased access to web-based mapping tools have made it easier for the general public and professionals to create maps with little GIS background.

20.4 Benefits of Applying GIS to Monitor and Manage Pandemics

Some of the earliest medical maps were made in the seventeenth century, such as those for the plague in Naples around 1690 when mapping was an expensive pursuit (Koch 2005). Since the 1960s, when GIS became computerized, it became possible to easily visualize disease movement and prevalence (Kamel Boulos and Geraghty 2020). Other examples of prior GIS usage include studies that employed geospatial analyses to map travel times to healthcare facilities, especially for more vulnerable populations in sub-Saharan Africa to help manage Ebola (Hulland et al. 2019). GIS systems can utilize spatial statistics, spatial models, and cartography to describe populations, movements, and other aspects of disease-induced changes to help us monitor and manage the effects of pandemics around the world (Musa et al. 2013). Data is now easily transformed for easy and quick visual interpretation for public health surveillance. GIS is a powerful aid, especially in the current COVID-19 pandemic, to identify hotspot outbreaks, at-risk populations, resource accessibility, to improve information spread, and to create an information system for pandemics (Burton 2020, Roy et al. 2020). Jack Dangermond, the founder of ESRI, reported that he is very proud of the work the GIS community is doing in responding to this pandemic (Burton 2020).

Epidemiology is one of a wide variety of fields to which GIS has been applied (Maguire 1991; Figueiredo et al. 2020). Epidemiological surveillance systems were first developed by the U.S. Peace Corps to help provide important information to field staff starting in 1985. By 1995, they developed GeoSentinel®, which collects global data for surveillance of travel-related morbidity in collaboration with the CDC (Gamble and Lovell-Hawker 2008). Global observation data has been collected for previous epidemiological studies such as measles, human immunodeficiency virus (HIV), and viral hepatitis for patients with hemophilia (Patel and Orenstein 2019; Schieve et al. 2020). Epidemiological surveillance is also used to collect health-related data that can be analyzed and interpreted to aid in planning decisions about disease prevention and control. This data is useful to analyze geographical hotspots of disease cases and outbreaks. The SARS outbreak of 2003 led to development of methods to report disease cases on a global level (Burrell et al. 2016). For example, WHO now maps polio cases yearly while showing trends over time (WHO; http://polioeradication.org/polio-today/polio-now/). Contact tracing was employed to actively identify cases and monitor the spread of infection, such as for Ebola, and is now being applied to COVID-19.

During the COVID-19 pandemic, many sources and researchers have accessed the global surveillance data to produce websites that show many types of daily statistics (Ahasan et al. 2020). Due to the importance of mapping applications in epidemiological studies, increasing numbers of public health papers that employ GIS are likely to appear in the coming months, and 7 have already been documented in a recent review of 79 different geospatial-based research articles on COVID-19 (Ahasan et al. 2020). Unfortunately, for previous epidemiological studies, there were some technical restrictions that greatly limited some of the geospatial analysis that could be produced.

20.5 Previous Limitations to Epidemiological GIS Analysis

Some of the previous epidemiological studies prior to COVID-19 had spatial and data processing limitations that are now less restrictive. For example, medical bioinformatics experience fewer limitations in transferring huge amounts of data to the Cloud as servers grow in their ability to store large amounts of data, which was a limitation dating back to 2012 (Dai et al. 2012). Improvements include fog computing, developed by CISCO in 2014, that helped improve cloud computing by reducing the distance issues of how far away a user was from the cloud server (Yi et al. 2015). Further improvements to high-speed Internet allow the quick download of large quantities of data that can be provided to the general public and researchers for little to no cost.

The term "big data" has been used to refer to datasets that are too large for the typical database to store and analyze (Manyika et al. 2011; Musa et al. 2013). It was suggested that if the healthcare industry could use big data technology effectively then costs would be greatly reduced (Manyika et al. 2011). Starting from the 1990s, medical GIS has been growing in popularity to help forecast public health issues (Musa et al. 2013). The Johns Hopkins COVID-19 dashboard website taps into the big data potential to provide information about COVID-19 to the world (Dong et al. 2020, Johns Hopkins; https://coronavirus.jhu.edu/map.html). GIS and big data technologies have been combined to provide near-real-time visualizations of the pandemic around the world for monitoring purposes. These software and technology improvements over the last decade have paved the path for the rapid production of GIS systems for the pandemic.

Space–time analysis enables examination of distributions of events, such as disease spread over specific time periods and locations (Musa et al. 2013). For surveillance during this pandemic, a space–time scan statistic has been constructed to show the presence of cases and emerging clusters of COVID-19, and track them through space and time (Desjardins et al. 2020). This is a valuable resource in aiding resource allocation, testing, and monitoring of disease spread. Some dashboards for the COVID-19 pandemic are updated daily, allowing for near-real-time predictions and analysis to aid healthcare professionals and the general public (Desjardins et al. 2020). In contrast, space–time data were considerably limited for GIS epidemiological studies between 1999 and 2013 (Moore and Carpenter 1999; Musa et al. 2013).

Previous GIS software versions also limit the size and scope of statistical analysis and space–time analysis. Links between "R," a programming language, and GIS software or other statistical packages like S-Plus for Arc/Info as well as software that adds GIS techniques into a statistical package like (SAS/GIS) have decreased such limitations (Waller 1996). In 2013 the spatiotemporal dynamics of influenza outbreaks were visualized by using a random network methodology implemented within the R and GIS systems (Ramírez-Ramírez et al. 2013).

20.6 GIS Concepts of Importance for COVID-19 Studies

Combining many layers of discrete and continuous spatial data such as roads, lakes, cities, elevation, and even precipitation measurements results in the creation of GIS maps. Discrete data is one type of spatial data that includes definable mapped areas having fixed locations, such as property boundaries and roads. This data can be represented with either vector or raster data.

Vector data uses a series of *x–y* coordinates stored as points, lines, or polygons, which are as accurate as the gathered *x–y* coordinates (Price 2004). Vectors can be very precise as they can store up to six decimal places (Price 2004). Raster data is a grid of cells all holding a value for the same attribute; it is similar to a picture of an area where every pixel is a square of the Earth's surface and holds a value to represent some feature of that area such as elevation or temperature (Price 2004).

It is important to consider the resolution of a raster grid as larger cell sizes limit the ability to detect change across the landscape to that cell size. For example, a raster with a 100 m resolution is made up of cells that each represents a 100 m^2 area with one value for some attribute. While it is valuable to have higher resolutions to more accurately portray change across the land, smaller cell sizes can dramatically increase file size and processing time for analysis. It is important to consider the type of data layer that is used when making a map as there are varying advantages and disadvantages based on the research objectives for the analysis. Data layers derived from different sources may have different levels of accuracy, which must be considered when making a map since the lowest level of accuracy dictates the accuracy of the produced map (Goodchild and Longley 1999).

Remote sensing involves measurements of different characteristics of an object from a distance by using electromagnetic energy reflected from, or emitted by, an object and then recorded by an observer or instrument that is not in contact with the object (Mather and Koch 2011). Generally, measurements of objects on the Earth's surface are made from sensors mounted on aircraft or on satellites. Remote sensing systems usually collect raster-based data.

When creating maps, it is important to consider how the data will be displayed. Important components of a map include scale bars, direction labeling, and a legend. The spatial scale, or the map's extent, is important to determine for the study area and desired analysis. Many of the COVID-19 maps use the world as their extent. Luckily, world-scale maps de-emphasize effects of generalization and other map errors (Monmonier 2018). On a world map, usually a small-scale map, a square measuring 1 in. on each side most likely represents a bigger area than for a country map, or a larger-scale map, where a 1-in.^{2} represents a much smaller area. Thus, the country map will have much greater detail than a world map, therefore having less generalization. Scale bars are added to help measure components on the map to show how the scale of the map compares to real-world measurements (Peterson 2014). A north arrow is a common way to give a sense of direction, which helps the user orient themselves to the map. Finally, the legend lets the reader know the meaning of symbols and colors in the map.

The book *How to Lie with Maps* by Mark Monmonier (2018) discusses how maps are not always accurate as they necessarily make generalizations about what they are presenting. When creating or viewing a map, it must always be considered how the colors, symbols, phrasing, and point of view are influencing the reader's understanding. For example, red is a common color to use for danger and urgency that can influence a reader to feel more alarmed about the data. The value and accuracy of a map also depends on how well the geometric generalization depicts reality (Monmonier 2018). Global scale maps will have more generalization as line and point layers will not be able to show all the details that a country map can show, such as for roads, which may only be shown as interstates on a global map. It is very easy for anybody to make a map and not consider some of the basic GIS concepts in the process (Buckley and Field 2011; Norheim 2012). The result could lead to inaccurate analyses or results.

Several concepts of spatial data are important to consider when searching for data to make a map. The user needs to consider the accuracy of any located data layers as maps produced will only be as accurate as their data. Data mining is the ability to obtain data at high-speed rates for a particular interest (Goodchild and Longley 1999). An example described by Ahasan et al. (2020) considers the mining of Twitter data containing tweets reporting COVID-19 symptoms of users in relation to COVID-19 testing accessibility (Andrade et al. 2020). Geodatabases are a helpful tool when gathering different sources of data or map layers to include in a map. A geodatabase can efficiently store different layers that are collected from a variety of sources (Price 2004). The usefulness of a GIS system depends on choosing and matching the correct world projections to display the data based on the intended analysis (Price 2004). Different projections can change how one assesses the size of different areas relative to one another, which could lead to distortions on how the map is interpreted (Field 2020). The mapmaker then has to re-project or transform all the data layers to have the same projection so that the data accurately lines up for analysis. Conflation is when functions are applied to resolve issues associated with the merging of different datasets (Goodchild and Longley 1999). A geodatabase can be used to help ensure all data layers have the same projection, cell size, or data extent.

GIS can also include network analysis of path systems like roads, streams, sewer pipes, etc. (Price 2004). This is a helpful tool that can be used, for example, to determine the quickest and most efficient path from a home to a COVID-19 testing center. This tool can even incorporate speed limits, traffic, and time of day for travel.

A mateurs who do not know basic GIS concepts, or do not have a background in cartography, have created COVID-19 maps. Such maps can contribute to a pandemic infodemic (an excessive amount of information, in which some of it is accurate and some is not), which makes it hard to analyze what is accurate or representative of the current situation (Mooney and Juhász 2020). ESRI, through ArcGIS online, is hosting COVID-19 online map-making classes, which is a valuable resource, but it can also make it more likely for the layman to make maps (Rosenkrantz et al. 2020). Caution needs to be used in reviewing different models, maps, and other GIS technologies that are being developed hastily now to convey information during the pandemic.

Many choropleth maps have been produced to depict COVID-19 cases around the world and for other related subjects. Choropleth maps, often considered graduated color maps, use a pattern, shading, or a symbol within a set area to show different classifications of data as a summary or generalization of reality; because of the generalizations needed for such representation, there has been considerable debate on their accuracy (Jenks and Caspall 1971; Monmonier 2018). Many maps for the pandemic have used absolute values to show the number of cases across a country with a choropleth thematic mapping technique. This is known to lead to accuracy issues as different areas have different numbers of people in it leading to inaccurate conclusions when looking at a choropleth map (Field 2020; Franch-Pardo et al. 2020). Another source of error for choropleth maps is when the map maker uses the "default" classification scheme for creating classes (or different patterns) for the map, instead of figuring out which type of breaks or classes make the most sense for what is being conveyed (Monmonier 2018). Model accuracy is "the credibility of long-term projections generated by quantitative models" and is constantly debated (Eker et al. 2018). The model should accurately reflect the observed data (Eker 2020).

Population normalization can solve some of the accuracy problems of creating a choropleth map based on raw numbers (Field 2020). It is achieved by dividing the number of cases by the population in a specific area to give a percentage of that area that has been infected. Otherwise when visualizing the data with only raw numbers, some areas can appear to have very few cases, but instead have a high percentage of infection if that area has a low population.

Some types of choropleth maps are more accurate if they are derived from statistical distributions by dividing an area into subregions. The method of classification for the data greatly influences the accuracy. Jenks and Caspall (1971) describe the amount of error of a choropleth map based on a series of error prisms that relate to the real data and the generalized model and can be calculated based on the sum of the volume of these prisms. In this case, a greater number of map classes may increase accuracy (Jenks and Caspall 1971). However, maps can also become so complex that they no longer serve their purpose (Jenks and Caspall 1971).

An isopleth represents a changing attribute over an area where that attribute is the same magnitude between two isopleth lines. A contour map is an example of an isopleth map where the elevation changes, typically in some multiple of 10, with each new contour line. This is similar to a raster where the entire area will hold a value for that attribute, but a raster is more detailed since each "pixel" of area can hold a different value.

Kriging is another method of spatial interpolation that estimates values at unknown points based on the values at known points (Cressie 1986). It assumes that the direction or distance between samples reflects their correlation. Common examples include precipitation maps where rainfall points measured at weather stations are interpolated to produce a raster of continuous rainfall estimates across that area. It creates a raster surface by inputting points that have a recorded z-value. A

z-value is typically an elevation measurement of a surface at location (x, y); however, the z-value can be any measurement that you are studying at that point location. These commonly used terms and interpolation methods should be considered when reviewing maps made for the pandemic.

20.7 Current COVID-19 Near-Real-Time Maps and Dashboards

Space–time representation in maps is one of the current frontiers in the evolution of GIS and is considered by many to be an essential component of the spatial analysis of disease patterns in the future as technology and data sizes grow (Musa et al. 2013). Now with near-real-time mapping of COVID-19 cases and mortalities, the space–time limitations seem to be largely resolved.

Online dashboards are increasingly utilized now as tools to inform the general public and healthcare professionals about the spread of COVID-19. Dashboards have become incredibly popular during the pandemic partly due to the social confinement of staying at home (Mendoza 2020). Many of these dashboards map the number of cases, deaths, or recoveries over time.

Gardner and Dong at Johns Hopkins University, Baltimore, MD, USA, in collaboration with ESRI, created the COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) to track COVID-19 cases in near-real-time since January 2020 (Fig. 20.1) (https://coronavirus.jhu.edu/map.html). The dashboard displays the number of cases, deaths, and recoveries from different

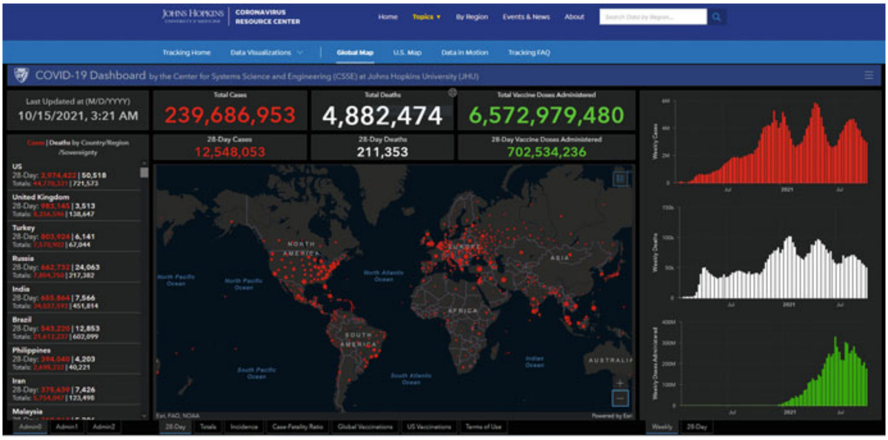

Fig. 20.1 COVID-19 dashboard created by the Johns Hopkins Centers for Civic Impact Engineering (CSSE) tracking COVID-19 in near-real-time in collaboration with ESRI, who acquired the data from WHO, the U.S. Centers for Disease Control and Prevention, the European Center for Disease Prevention and Control, the National Health Commission of the People's Republic of China, 1point3acres, worldmeters.info, BNO, state and national government health departments, local media reports, and the DXY, one of the world's largest online communities for physicians (This screenshot was taken from https://coronavirus.jhu.edu/map.html) on October 15, 2021, with permission to reproduce)

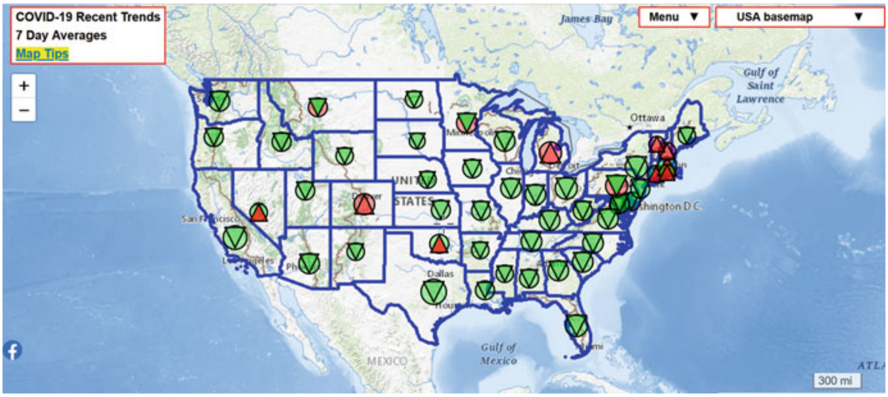

Fig. 20.2 Website shows the COVID-19 daily cases that are averaged over the previous 7 days based on the time series data that Johns Hopkins University updates daily. Based on these averages, the map uses red symbols to show the states where the number of cases is increasing (negative trend) and green symbols to show the states where the number of cases are decreasing (positive trend). This website has different map layers that can be turned on or off, for example, to show the location of testing centers, the number of available hospital beds, and more. (This screenshot was reproduced from (https://bit.ly/36zraWN) on October 15, 2021, with permission from Joseph Elfelt, creator of https://mappingsupport.com/)

countries around the world using a GitHub repository (JHE CSSE) and initially was updated twice a day (Dong et al. 2020). ESRI's ArcGIS Living Atlas team helped to add a "semi-automated living data stream strategy," which aggregates local sources to track cases of COVID-19 in near-real-time with some locations updated in 15-min increments and others updated manually (Dong et al. 2020). The website uses data from many different sources including WHO, the CDC, the European Center for Disease Prevention and Control, the National Health Commission of the People's Republic of China, 1point3acres, Worldmeters.info, BNO (BNO news), state and national government health departments, local media reports, and the DXY, which is one of the world's largest online communities for physicians, healthcare professionals, pharmacies, and facilities (https://coronavirus.jhu.edu/map.html and https://coronavirus.jhu.edu/map-faq). While millions of users have used it to monitor the pandemic, it, unfortunately, does not display maps of the data for previous dates (Kamel Boulos and Geraghty 2020). Other limitations of this website are that it may load slowly and viewing is difficult on smaller mobile devices.

A different perspective on pandemic data is obtained using an online web map produced by Elfelt (2020a). This map uses the time-series data that Johns Hopkins University updates daily and publishes on their GitHub site (Fig. 20.2). The advantage of this website is that, instead of showing the cumulative counts of cases like the John Hopkins website, it can show COVID-19 daily counts that are averaged over the previous 7 days. Averaged counts for the previous 2 weeks are produced by code that automatically runs each night. Based on this averaging, the map uses colored symbols to show if the recent number of cases or deaths is generally increasing or decreasing (Elfelt 2020b). This is calculated by taking the daily counts over the last 7 days and plotting these points on a graph. The x values refer to days and can have values 1–7. The y values are daily counts. The scripting determines the slope of a line that "best fits" the points. If the slope is positive, the trend is increasing; and if the slope is negative, the trend is decreasing.

Previously, the map did not use the time-series data or plot the average number of cases over 7 days, which led to some errors. Averaging is helpful as some health departments do not report their COVID-19 statistics on a daily basis and the lack of reporting during holidays or weekends may lead to a larger number of cases on a Monday, which can negatively impact the calculation that determines if cases are increasing or decreasing (Elfelt 2020b). For locations that have an increase in cases, there is a red symbol (negative trend), and for areas that have a decreasing number of cases (positive trend) there is a green symbol. This website also contains different map layers that can be added or deleted to show the recent trend data for cases or deaths by county, state, or totals for the United States, as well as testing locations, number of available hospital beds, and more (Fig. 20.2). While some of this information is also widely available from the Johns Hopkins website, it is much faster to load and more mobile-friendly (Elfelt 2020c).

Several statewide dashboards, or near-real-time monitoring websites, have been developed to help monitor the pandemic. The Washington State Department of Health's King County dashboard visualizes a vector-based choropleth map on which confirmed cases, hospitalizations, and deaths are displayed in varying shades of color for each county; representing the magnitude of that category in the county (Washington State Department of Health; https://www.doh.wa.gov/Emergencies/COVID19/DataDashboard). For more detailed information within a county, the user is directed to Local Health Departments, such as the King County Public Health COVID-19 dashboard. Under the geography portion of the King County daily COVID-19 outbreak summary, an interactive map displays data on the most current confirmed positive cases, test positives, hospitalizations, deaths, all test results, and number of people tested by the user-selected areas of city limits, health reporting areas, zip code, or census blocks (King County; https://www.kingcounty.gov/depts/health/covid-19/data.aspx).

Some of the near-real-time online dashboards are less accurate than others. Their temporal accuracy can change over time because the number of cases or deaths may be less accurate over the course of weekends and holidays when the reporting centers update results less frequently (Murray et al. 2020). For example, in King County, Washington, poor air quality, during the wildfires, in the Puget Sound region was listed as a limitation for case and mortality accuracy in September 2020 on the online dashboards since they stated many testing sites were closed (King County; https://www.kingcounty.gov/depts/health/covid-19/data.aspx).

Aside from temporal inaccuracies, the data itself can be a major source of error. Inconsistent health data and reporting discrepancies for mortalities is leading to inaccurate analyses or hard to interpret results (Rosenkrantz et al. 2020). Such as when the State of Washington changed their COVID-19 death reporting methods, which increases the difficulty of following trends over time (Washington State

Department of Health; https://www.doh.wa.gov/Emergencies/COVID19/DataDashboard). Previously, deaths were associated with COVID-19, if the patient tested positive for the virus while they were in the hospital, and even if the patient died of another medical issue like a stroke (Washington State Department of Health; https://www.doh.wa.gov/Emergencies/COVID19/DataDashboard). There are false perceptions that these dashboards or spatial visualizations are completely accurate and their usefulness may be greater than it is (Rosenkrantz et al. 2020).

The *New York Times* interactive COVID-19 maps may be more representative than some of the other dashboards or websites as they normalize the data by reporting the average daily cases per 100,000 over the past week for the world (Almukhtar et al. 2020). They also have several additional tables and charts that further enlighten the public about the COVID-19 pandemic across the globe.

The National Response Portal accesses Google Cloud, which combines data from many public and private sectors, to provide a location for healthcare professionals to access local COVID-19 data in making decisions about the pandemic (Vigliarolo 2020). The portal includes maps that scale down to the county level, are updated daily, and show forecasts for the number of cases and hospitalizations that is normalized per 100,000 people (National Response Portal; https://map.nationalresponseportal.com/portal). It shows mobility data for counties based on different categories like parks and workplaces. Many healthcare agencies help supply the data it provides (Vigliarolo 2020).

20.8 Environmental GIS Applications During the Lockdowns

20.8.1 Impact on Wildlife Movements

University of California Davis's (UC Davis) Road Ecology Center has created detailed reports about how the "stay-at-home," or lockdowns, reduction in traffic patterns has impacted wildlife-related vehicle collisions (https://roadecology.ucdavis.edu/). This center used traffic data from StreetLightdata.com and collision data from California, Idaho, and Maine to determine if vehicle collisions with wildlife were reduced with the stay-at-home orders. Miles traveled by drivers in the United States were reduced from 103 billion miles in March 2020 to 29 billion miles in the second week of April 2020, which resulted in approximately a 71% reduction in travel (UC Davis; https://roadecology.ucdavis.edu/). For the three study states, there was a 63–75% reduction in the amount of driving during this time.

This study also compared the wildlife-related collisions from 4 weeks before the stay-at-home orders were put into place to until 4 weeks afterward (Nguyen et al. 2020). The results were compared to other years as well, and the number of wildlife-related injuries was far fewer as a result from the reduction in traffic. The study predicted that 5700–13,000 fewer large mammals could be killed per year, and in California alone, 50 fewer mountain lions could be killed per year. There was a 58% reduction of mountain lion collisions in California based on the vehicle traffic changes from 10 weeks prior to the issued stay-at-home order until 10 weeks afterward. The results showed a statistically significant reduction in vehicle related wildlife collisions of approximately 21–58% in California, Idaho, and Maine (Nguyen et al. 2020).

There are several caveats the study describes when considering wildlife-related mortalities with vehicles as there is not necessarily a linear relationship between collisions and traffic volumes. The study did not look at collisions with all types of large animals or animals of all sizes. The study did not notice geographical differences in where the number of vehicle collisions and the reduction in collisions decreased. It should also be considered that some individuals are driving faster than normal due to reductions in traffic from stay-at-home orders for the pandemic. Perhaps as a result, some areas are seeing an increase in the number of animal injuries from speeding cars. Between 2013 and 2019, Yosemite reported an average of 24.4 bears were hit per year (National Park Service; https://www.nps.gov/yose/learn/management/statistics.htm). In August 2020 alone, at least four bears were injured from speeding cars in the park (Sanchez 2020).

The pandemic has also led to various reports of changes in animal activity due to changes in human movement patterns from the lockdowns (Rutz et al. 2020). Google has created "COVID-19 community mobility reports" (https://www.google.com/covid19/mobility/), which can be applied to wildlife movement patterns. For example, there appears to be a mobility trend of −5% for humans, after the pandemic started, compared to baseline in park visits in certain areas. These trends are calculated over a several week period and are generally based on the "location history" of someone's mobile technology (Google Community Mobility Report; https://www.gstatic.com/covid19/mobility/2020-11-24_AF_Mobility_Report_en.pdf).

Another initiative is collecting stories about how animals are responding to changes in human activity due to measures used to control the spread of coronavirus. An international consortium has been formed, the "COVID-19 Bio-Logging Initiative" (www.bio-logging.net), which is collaborating with the Movebank online research platform and the Max Plank Institute of Animal Behavior, to use "bio-loggers" to record changes in animal movement and behavior in relation to changes in their environment due to the pandemic (Figs. 20.3a, b) (Kranstauber et al. 2011; Wikelski et al. 2020). The Movebank platform, as of March 2020, included over 2.4 billion locations and over 989 taxa (Kranstauber et al. 2011). Often, data from smartphones is used to derive GPS tracking logs in combination with required field data (Rutz et al. 2020). Most of the studies, unfortunately, are not yet available to the public as it is up to the scientist if they would like them to become available. The Animal Tracker app (available for Android, iPad, and iPhone) allows anyone to see their animal observations with live monitoring and to give permission to allow the general public to see them (Wikelski et al. 2020).

Impacts of the stay-at-home lockdowns on animal movement and behavior are having a positive and negative impact on wildlife. According to Movebank, some species that rely on urban environments, or the protection of humans, will suffer from the lack of people (Max-Planck-Gesellschaft; https://www.mpg.de/15005457/covid-19-lockdown-reveals-human-impact-on-wildlife). Rats, raccoons, birds, and other common city critters that rely on human refuge in urban environments are

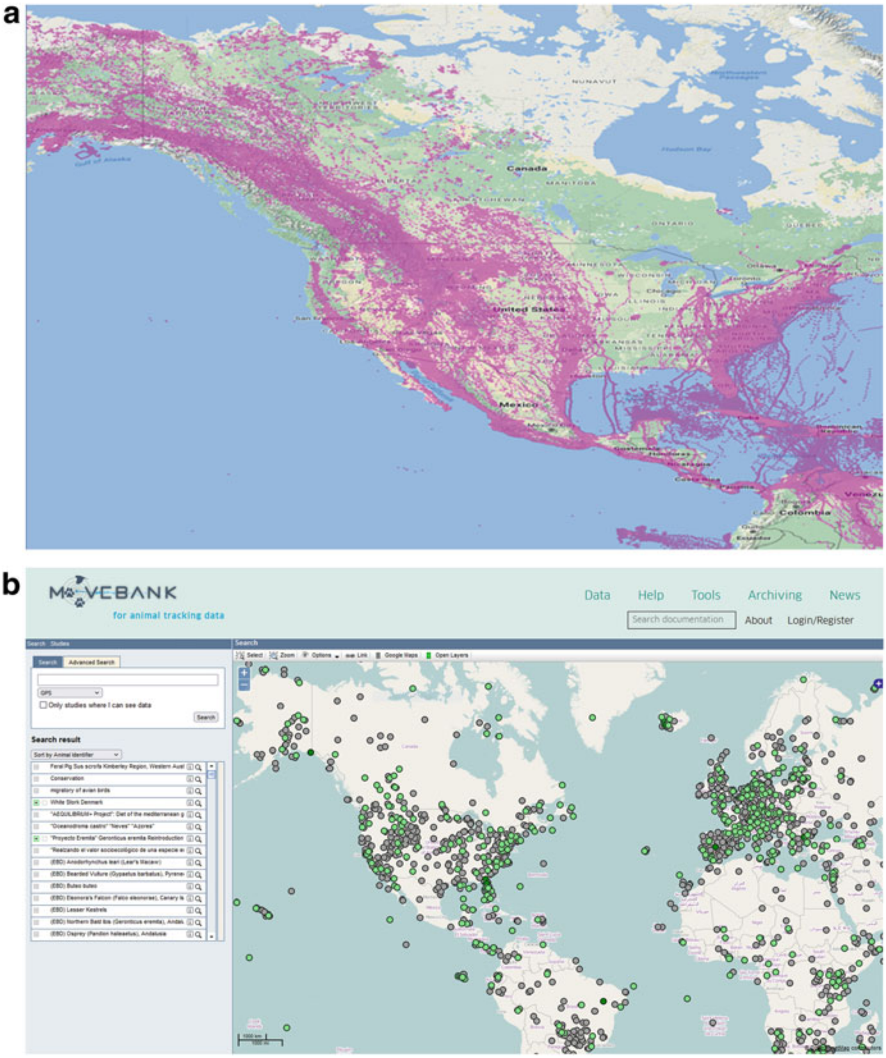

Fig. 20.3 The Movebank online database platform stores and shares animal movement data and bio-logging data, based on a variety of animal studies hosted by the Max Planck Institute of Animal Behavior. Image of the Movebank online platform for animal movement data (Kranstauber et al. 2011). (This screenshot was reproduced from https://www.movebank.org/cms/webapp?gwt_fragment=page=search_map with permission on October 15, 2021)

experiencing increased stress due to the lack of access to food. Endangered species such as rhinos or elephants can be exposed to increased risk of poaching due to the lack of human protection and presence (Max-Planck-Gesellschaft; https://www.mpg.de/15005457/covid-19-lockdown-reveals-human-impact-on-wildlife). Other species have benefited by the reduction of humans in their environment, such as in forest service parks and other popular outdoor tourist areas. Movement of these species and related behavior can be investigated using GPS, and compare their range pre, during, and post stay-at-home initiatives. The mass human behavior changes with COVID-19 have provided a unique time to study the human–wildlife interface, which will be sure to produce valuable research findings, as well as other environmental studies of the lockdowns.

20.8.2 Impact on Air Pollution

Air quality studies have been conducted to compare air pollution levels during the strictest stay-at-home lockdown periods of the pandemic with the pre- or post-lockdown periods. Many of these studies resulted in fewer emissions during the lockdowns. There has been a decrease in air pollution, specifically nitrogen dioxide and carbon dioxide levels during the pandemic (McMahon 2020). The UC Davis Road Ecology Center did an additional study on how much greenhouse gas emissions were reduced based on the stay-at-home orders for COVID-19 (Shilling 2020). The study found that there was a 61–89% reduction in daily miles traveled in the United States during the peak of the stay-at-home orders. California alone saw a 75% reduction in daily travel that reduced greenhouse gas emissions (Shilling 2020). The reduction in greenhouse gas emissions during this time period can aid California toward creating strategies to meet the goal of reducing greenhouse gas emissions by 80% in 2050 (Shilling 2020). A week before the March 2020 lockdown, carbon dioxide emissions were measured at 44 million metric tons (Shilling 2020). Then by the second week of April 2020, after the stay-at-home order was issued, carbon dioxide emissions were down to only 12 million metric tons (Shilling 2020). This was a 71% decrease in emissions based solely on vehicle traffic (Shilling 2020).

Another study in Italy utilizing remote sensing technologies showed a decline in air pollution, particularly nitrogen dioxide, during the lockdown for COVID-19. A Copernicus Sentinel-5P Tropomi satellite showed the imagery in Europe from January 1, 2020, until March 11, 2020, using a 10-day moving average. The study describes this satellite as currently being the most accurate instrument available to measure air pollution from space. The study was confident that the changes seen were from the lockdown restrictions and not likely from cloud cover or weather changes (Fig. 20.4) (European Space Agency; https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P/Coronavirus_lockdown_leading_to_drop_in_pollution_across_Europe).

Measurements from the European Space Agency's Sentinel-5P satellite showed that nitrogen dioxide levels in Asia and Europe were reduced as much as 40% in January and early February 2020 (Monks 2020). When the United Kingdom announced a nationwide lockdown on March 23, 2020, nitrogen dioxide levels fell as much as 60% compared to 2019 levels (Monks 2020). In the United States, many cities also saw a decrease in nitrogen dioxide. NASA reported a 30% reduction in New York compared to 2015 and 2019 levels (Monks 2020). Los Angeles was down 33%, followed by New York at 22% and Seattle at 19% (Gardiner 2020). A 40%

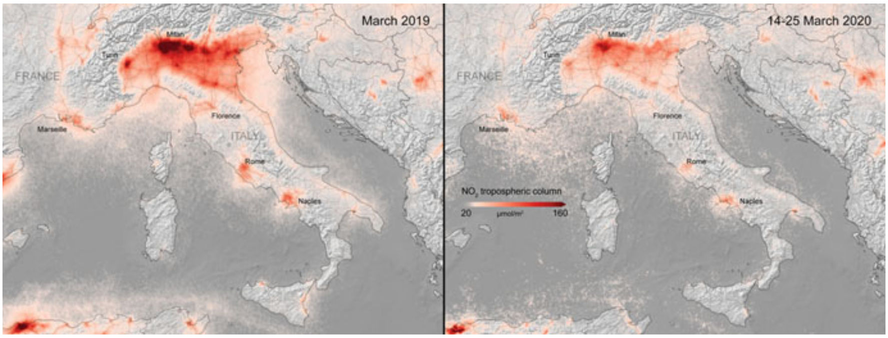

Fig. 20.4 Remotely sensed imagery from the Copernicus Sentinel-5P satellite showing the reduction in monthly average concentrations of nitrogen dioxide (NO) over Italy (**a**) from March 2019 (pre-lockdown) to (**b**) March 2020 (during the lockdown) (ESA 2020). (This figure was reproduced from http://www.esa.int/ESA_Multimedia/Images/2020/03/Nitrogen_dioxide_concentrations_over_Italy with permission)

drop in nitrogen dioxide levels is comparable to removing 192,000 cars from the road (Monks 2020). Areas that averaged even one microgram per cubic meter more PM2.5 particulates were shown by Harvard Universities T.H. Chan School of Public Health to have a 15% higher death rate from COVID-19 (Gardiner 2020). This is relevant to those on the US west coast who are regularly exposed to poor air quality from wildfire smoke pollution.

In Delhi, India, levels of PM2.5 particulates and nitrogen dioxide concentrations were 70% lower (Gardiner 2020). Parts of Europe, South Korea, and China saw reductions in nitrogen dioxide as well. However, the Ukraine, some African countries, and some other European countries saw an increase in these particulates (Gardiner 2020). In addition, China's improvement in air quality was temporary and has already returned to pre-pandemic lockdown levels (Gardiner 2020).

Air quality levels can be impacted by vehicle emissions. A 2017 study removed about 111,000 vehicle commuters from the Stockholm County, Sweden roads, and switched them to commute by bike (Johansson et al. 2020). This resulted in about an extra 449 years of life annually based on improved air quality from reducing vehicle emissions to commute by bike.

StreetLight data provides spatial datasets for different research studies relating to human movement, particularly to varying transportation methods (https://www.StreetLightdata.com/corona-bicycle-metrics/). One study used this data from StreetLight to determine if bike ridership has increased or decreased during the pandemic in the United States (Grogan and Hise 2020). The results were surprising: as bike ridership increased in the smaller metropolitan areas and ridership decreased in major metro areas that would generally have high ridership (Fig. 20.5). For example, some smaller cities not known for bike commuting, Ogden, UT, Lakeland, FL, Knoxville, TN, and other cities saw a huge increase. The results showed that the average trip distance was less than five miles, which is shorter than a typical exercise workout would be (Grogan and Hise 2020). In the small cities, it was found that

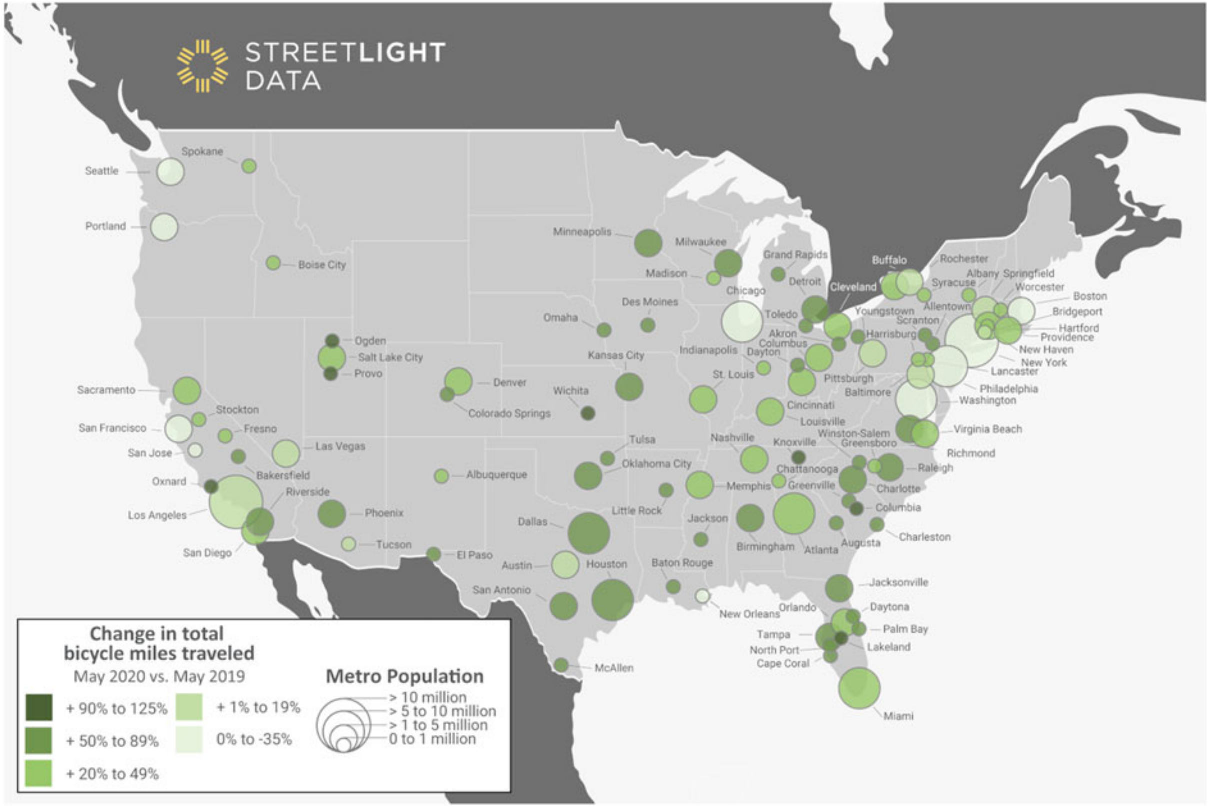

Fig. 20.5 Display of the difference in total bicycle miles traveled between May 2019 and May 2020 to demonstrate how miles traveled changed before COVID-19 lockdowns in 2019 and after lockdowns in 2020. Some of the smaller metro areas nearly doubled in miles traveled and some of the major metro areas declined in bike miles traveled. (This screenshot was reproduced https://www.streetlightdata.com/corona-bicycle-metrics/ with permission from StreetLight Data)

biking increased by the city center, indicating trips may have multiple purposes, such as for shopping to commute to work or other purposes. Whereas larger metropolitan cities, like Portland, OR, saw a decrease in bike trips. Bike trips decreased by 10%, a lot less than for vehicle motor traffic that fell by 35% (Grogan and Hise 2020). A more detailed analysis of bike ridership in Portland showed the biggest increase in ridership was by a mountain biking trailhead and ridership decreased by downtown Portland (Fig. 20.6) (Grogan and Hise 2020). A study in New York found a similar result where bike ridership through the shared bike riding system dropped by about 71%, much less than the subway ridership drop of about 90% (Teixeira and Lopes 2020). Evidently, the stay-at-home orders reduced both bike travel and vehicle travel in some areas.

20.8.3 Impact on Noise Pollution

WHO has said that environmental noise is one of the top environmental risk factors to health (WHO; https://www.euro.who.int/__data/assets/pdf_file/0008/383921/noise-guidelines-eng.pdf). WHO has set different standards to regulate environmental noises and recommend road traffic levels be kept below 53 decibels to reduce negative health impacts (World Health Organization; https://www.euro.who.int/__data/assets/pdf_file/0008/383921/noise-guidelines-eng.pdf?ua=1). In Dublin, Ireland, noise-monitoring stations recorded hourly average equivalent sound levels and maximum sound levels at 5-min intervals at 12 different locations during the pre-lockdown time period of January 1 to March 24, 2020, and during the lockdown from March 25 to May 11, 2020 (Basu et al. 2021). All 12 noise-monitoring stations showed a reduction in sound levels, which may be attributable to a reduction in road and air traffic during the lockdown. However, other environmental factors also could have reduced sound levels (Fig. 20.7) (Basu et al. 2021). Prior to the pandemic (January 1, 2020, to March 24, 2020), all monitoring stations recorded sound levels greater than 55 dB for more than 60% of the recording time (Basu et al. 2021). During the lockdown the percentage of time the sound levels exceeded 55 dB was greatly reduced (Basu et al. 2021) supporting less noisy transportation methods, like bikes in the future to reduce noise levels and associated health issues.

Another sound-level study is currently underway, which allows general citizens to participate by placing recorders on their residence in urban and suburban areas (Challéat et al. 2020). The data will be available to the public (https://osf.io/h285u/) through Open Science Foundation (OSF) (Challéat et al. 2020). The project has recorded sound levels during COVID-19 lockdowns and then during the resumption of normal activities.

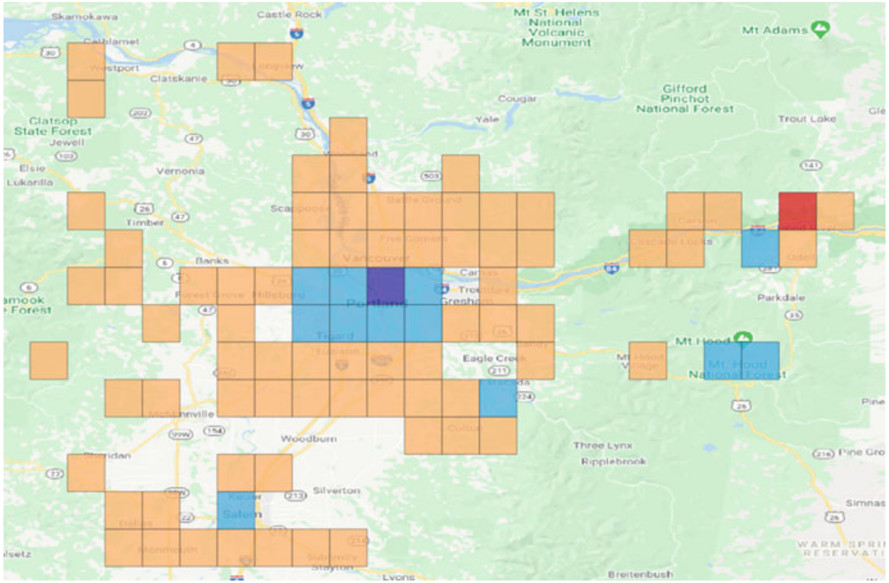

Fig. 20.6 This figure shows changes in bike ridership in the Portland, Oregon, area between May 2019, before the pandemic lockdowns, and in May 2020, during the lockdowns. The red square shows the biggest increase in ridership, where there was a mountain biking trailhead, the dark blue squares show where bike ridership decreased the most in downtown Portland, and the orange squares show where bike ridership increased. (This screenshot was reproduced from https://www.streetlightdata.com/corona-bicycle-metrics/ with permission from StreetLight Data)

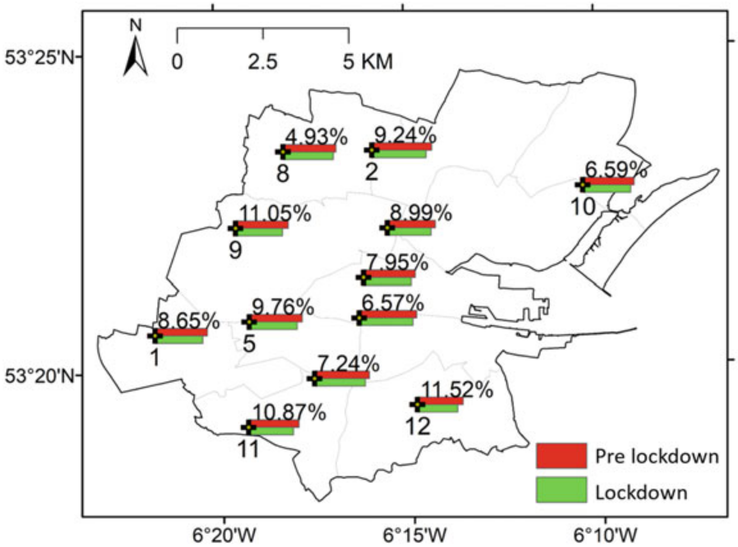

Fig. 20.7 This figure shows mean of hourly average equivalent sound level at monitoring stations in Dublin, Ireland, before the COVID-19 lockdown (January 1, 2020, to March 24, 2020) and during the lockdown (March 25, 2020, to May 11, 2020). (This figure was reproduced from Basu et al. (2021) with permission)

20.8.4 Impact on Water Turbidity

Satellite imagery can measure turbidity, chlorophyll, and colored dissolved organic material (CDOM) concentration in water bodies (Lim and Choi 2015). A recent remote sensing study used satellite data from the Sentinel-2 satellite, during the COVID-19 lockdown, to measure changes in turbidity along some of the most crowded stretches of the Ganga River in India (Garg et al. 2020). The Ganga River originates in the Himalayas and has connections to four surrounding countries, covering nearly one-third of the total geographical area in India. In many areas, the river is not considered clean enough for public drinking and it was found that the turbidity improved for water clarity at multiple locations along the river during the lockdown (Garg et al. 2020). In one region of the river, there was no rainfall to interfere with measurements between approximately mid-March to mid-April 2020, so the reduction in reflectance was likely due to a reduction in pilgrimage along the river (Garg et al. 2020).

20.9 Wastewater-Based Epidemiology

Due to the safety and financial concerns of the general public regularly going to a testing center for COVID-19, alternative or complementary testing methods and indicators of outbreak levels in a community have been explored. Wastewater

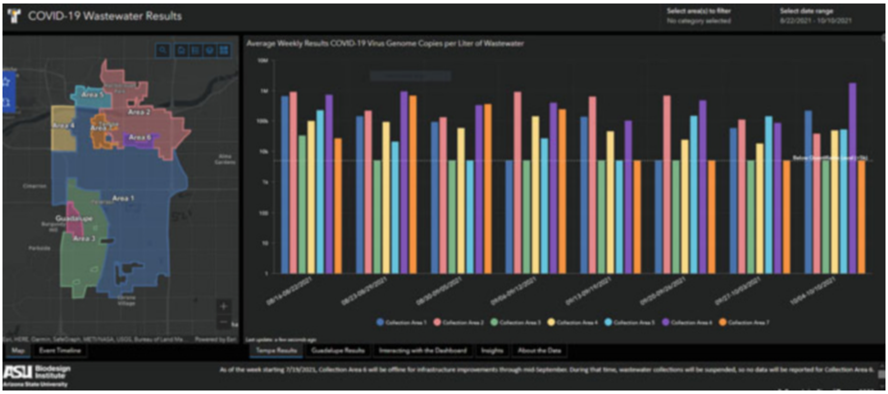

Fig. 20.8 Wastewater-based monitoring system under development in Tempe, AZ, designed to become, an early warning system to alert citizens when COVID-19 case numbers reach dangerous levels in their region. The leftmost panel of the figure shows the Tempe geographical regions, and the rightmost panel of the figure shows the average weekly results for COVID-19 genome copies per liter of wastewater from August 22, 2021, until October 10, 2021. (This screenshot was taken from https://tempegov.maps.arcgis.com/apps/dashboards/45f1871d65824746a46aa25ea5955a5f on October 15, 2021, with permission from the City of Tempe)

provides a unique venue for mass anonymous testing of COVID-19 for community health. Wastewater is the excess water from households or buildings, which includes toilets, showers, and sinks as well as from non-household sources like rain and industrial water that may contain human waste (CDC; https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/wastewater-surveillance.html). Taking samples at defined points and wastewater treatment plants is inexpensive and uses far fewer medical supplies than the current standard mass testing of individuals (Campbell and Wachal 2020; Hart and Halden 2020). The science behind this procedure is that COVID-19 sheds identifiable biomarkers in human waste that is detectable with regular wastewater testing (Hart and Halden 2020, CDC; https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/wastewater-surveillance.html). This helps pinpoint hotspots of infection since each test has a known mapped area that flows to that point. Using this method to identify hotspots allows for more efficient use of resources for individual testing and treatment in those areas.

Early in the pandemic, the CDC reported that the number of COVID-19-infected individuals in a region could not be determined based on sewage testing (Landers 2020). However, with new research, scientists determined that SARS-CoV-2 can be detected in the feces of infected individuals several days to a week or more before symptoms develop and can even be detected in asymptomatic individuals (Landers 2020). Now the CDC has a National Wastewater Surveillance System (NWSS) tool to which different states, governments, and tribal departments can submit their wastewater testing data to be input into a national database to help monitor the spread of COVID-19 (CDC; https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/wastewater-surveillance.html). Wastewater monitoring can complement existing COVID-19 direct testing of patients.

The City of Tempe, Arizona, now tests wastewater to detect COVID-19 biomarkers for different portions of the city (Lindemann 2020). Tempe has developed a publicly available dashboard that shows level of COVID-19 RNA in wastewater, with data collected several times per week (Fig. 20.8) (https://covid19.tempe.gov/). Hart and Halden (2020) are contributing to the knowledge behind COVID-19 wastewater testing with their research. The current working theory is that the COVID-19 biomarker can be detected from one infected individual in the wastewater received from a sample area with up to 2,000,000 people, depending on temperature and travel distance of the wastewater. For their research, Hart and Halden (2020) used the estimated COVID-19 biomarker load to wastewater (ratio) determined by Zhang et al. (2021) and Wölfel et al. (2020), as an input to a decay function for the COVID-19 biomarker. This decay function is used to determine how much of the biomarker remains over a given travel distance with a half-life dependent on the wastewater temperature. The wastewater layout system, structures, and population density were loaded into a GIS and combined with a previously built model that simulates a typical 72-h weekday load. This was used to create a new model to calculate in-sewer travel time, volumetric flow rate, and velocity and then was fed into the ESRI ArcGIS (GIS software) program. This information is used for each segment of pipe for the network analyst tool to analyze the accumulation and time of wastewater from households to the wastewater discharge point. The network analyst tool is used typically in complicated transportation routing problems, but the pipe network behaves similarly to transportation networks and can be treated similarly. Hart and Halden (2020) found that this would require in the worst conditions, at least 0.88% of the study population to be infected to produce successful detection of COVID-19 in the wastewater. With more optimal conditions of cooler temperature and shorter in-sewer travel time, only 0.00005% of the population would need to be infected for successful detection.

Wastewater treatment plants have definable service areas, using a discrete data layer, in the GIS database, so each plant is able to have at least a weekly test done to determine the load of COVID-19 RNA biomarkers present in the wastewater for each service area. While research for determining COVID-19 biomarkers is still in an experimental phase, the current results are promising and Tempe already has the infrastructure to implement this research in a real-world setting (Hart and Halden 2020; Lindemann 2020). For Tempe, there are six wastewater treatment plants each servicing different parts of the city, with the largest area servicing more than 183,000 households. Each service area could be further subdivided for testing to produce more detailed results and concentrations in the city (Lindemann 2020). This method provides a cost-effective, low waste, mass testing result to indicate various communities' health in the city.

Currently, other states in the United States and other countries, including the Netherlands and Australia, have also looked at wastewater detection of the virus in their attempts to reduce the impact of the pandemic. For the state of Massachusetts, the Massachusetts Water Resources Authority website shows Biobot Analytics', one of the first companies in the world to materialize data from sewage, analysis of two million customers in the Boston area (https://www.mwra.com/biobot/biobotdata.htm Hart and Halden 2020). Their measurements show a spike of the viral RNA in wastewater during April 2020, which dropped to half that level by November 2020, with samples taken three times a week (http://www.mwra.com/biobot/biobotdata.htm https://www.mwra.com/biobot/biobotdata.htm). The hope is that an early warning system can be derived to monitor COVID-19 case surges and provide a way to anonymously test for outbreaks. This method could be utilized in every city to help monitor viruses before they reach outbreak levels.

Water utilities continue to function under working environments affected by COVID-19, without disrupting customer needs for clean water and wastewater removal. GIS systems help these utilities manage their human resources to ensure workers stay safe while working remotely and to understand how COVID-19 is impacting their daily duties (Campbell and Wachal 2020). Employee locations and duties can be tracked, up-to-date communications can be provided to customers, and GIS can help identify future problems in service areas (Campbell and Wachal 2020). GIS dashboards, like those provided by ESRI, aid in tracking conditions in business facilities, workforce capacity, and communication needs. Personal and online COVID-19 data is used to visualize where the highest risk of exposure is in a utilities' service area, allowing for efficient resource allocation (Campbell and Wachal 2020).

20.10 Other GIS Applications

Several other GIS applications have been employed during the pandemic. Due to decreased transportation demands during the pandemic, the oil industry has suffered with very low prices for oil. Remote sensing technologies have been used to help determine the spatial location of crude oil reserves, particularly in Canada, to mitigate this effect and increase profits. Remote sensing can also be employed to help ensure that gas emissions from related extraction and processing follow environmental parameters (Gogeomatics; https://gogeomatics.ca/remote-sensing-the-potential-impacts-of-covid-19-on-oil-gas-sector/). Remote sensing has been used to detect underground pipe leaks by comparing daily vegetation health, around the pipes from collected red, blue, green, and near-infrared images (Wiseman 2019).

Another study used GIS and remote sensing to create COVID-19 risk indices based on many factors, such as hotspots, population density, access to clean water, and associated land use/land cover, which were related to COVID-19 levels in India (Kanga et al. 2020). Those that do not have access to clean water in their home have to leave home more often to get it, putting them at greater risk of exposure. ESRI's ArcMap (GIS software) was used to analyze the water well locations with a kriging spatial interpolation technique (Kanga et al. 2020). All of the layers were integrated with a GIS-based weighted overlay analysis. The produced maps showed where the risk was greater for the pandemic.

In the United States, one study determined which of 35 variables influenced COVID-19 cases at the county level across the United States (Mollalo et al. 2020). The variables that seemed to have a high influence on disease incidence were income inequality, median household income, the percentage of nurse practitioners, and the percentage of the black female population (to the total female population) at the county level (Mollalo et al. 2020). Many of the other environmental, socioeconomic, topographic, and demographic variables did not have as strong an influence on the number of cases at the county level (Mollalo et al. 2020).

20.11 Survey of Technologies Used to Monitor and Manage the Pandemic

20.11.1 Contact Tracing Apps

Due to many previous space–time limitations of epidemiological studies, such as limits with distance accuracy of census data, collecting smartphone movement data is currently being considered as a more accurate alternative to monitoring human movement patterns then previously used methods for health risk assessments and contact tracing (Deville et al. 2014). Digital contact tracing, such as through mobile technologies, is less labor intensive than for health departments to manually call potentially infected individuals (Smith and Mennis 2020). Using the data from mobile phones and other mobile technologies is very important when there is limited information available from a newly discovered virus (Ienca and Vayena 2020). There are more than 100,000 smartphone-based health-related apps available (Faezipour and Abuzneid 2020). In 2019, a new mobile program (mHealth) was used to test how easy it was to use mobile phone data to monitor human movements and assess the real-time health risk for infections during travel (Lai et al. 2019).

With the proliferation of smartphone use around the world, the pandemic has resulted in the production of many contact tracing apps around the world for use by the general public. These apps warn individuals that they may have encountered an infected individual. It is warned that these apps may not be as effective in a highly populated region where the virus is widespread compared to a less populous area at an early stage of the outbreak, where quarantining infected individuals is more effective (Servick 2020). Contact tracing is being widely utilized around the world, especially in developed countries, as of November 14, 2020, to help monitor the pandemic (Fig. 20.9).

For example, China has developed a “close contact detector” app that uses big data from the movement of people, such as from transportation data and COVID-19 disease records, to see if someone was in close contact with an infected individual in the last 2 weeks (Kamel Boulos and Geraghty 2020). Data privacy issues were not as much of a concern as they have been in other countries as China considers it a benefit for the greater good (Kamel Boulos and Geraghty 2020).

India, on the other hand, has developed considerably more contact tracing apps (Mitter 2020). The Test Yourself app records information when patients book

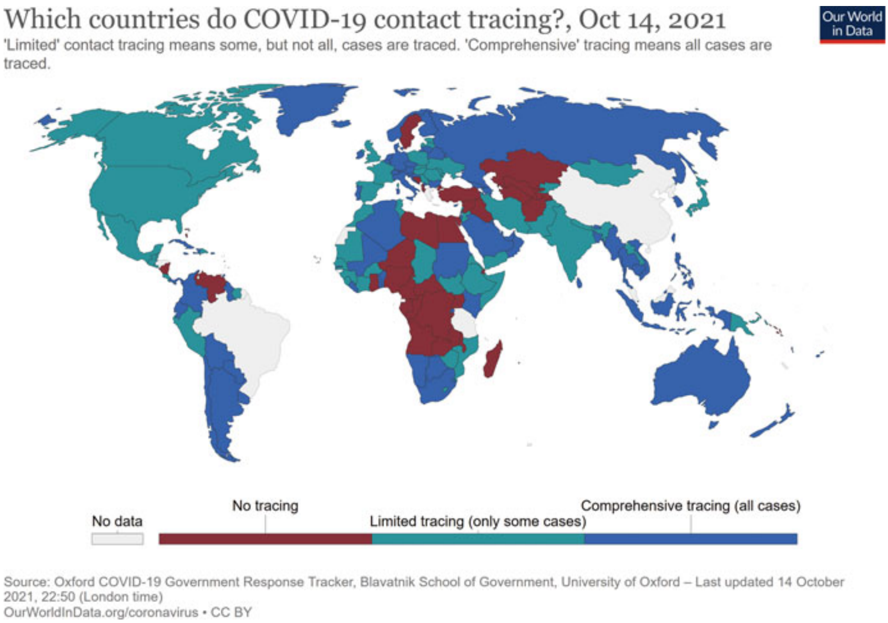

Fig. 20.9 This map shows worldwide usage of contact tracing to warn individuals about encounters with a COVID-19-infected person in their daily activities, which may have exposed them to the virus. Dark blue-colored countries on the map have comprehensive tracing, where tracing is performed for all cases, aqua-colored countries have limited tracing, where tracing is performed for only some cases, and red-colored countries do not perform tracing for any cases. (The figure was reproduced from Our World with Data (https://ourworldindata.org/grapher/covid-contact-tracing?time=2021-10-14 on October 14, 2021, with permission)

medical appointments; users can answer questions about symptoms of the virus they are experiencing and it gives related advice (Mitter 2020). It had at least 50,000 downloads and is available in several languages. The COVA Punjab app helps monitor citizens that are under quarantine and alerts authorities if the person strays over 100 m from their home location (Mitter 2020). It has had over half a million downloads and at one point ranked in the Top 10 "health and fitness" apps on the Google Play Store (Mitter 2020). The Aarogya Setu app reached more than 50 million downloads as a contact tracing app, available in 11 languages, that alerts people when they are within 6 ft. of a known COVID-19 patient (Mitter 2020).

In Germany, the Corona-Warn-App was commissioned by the Robert Koch Institute who partnered with Apple and Google to create it (https://www.coronawarn.app/en/). It uses a mobile device that broadcasts a rolling proximity identifier, or encrypted random codes, and looks for identifiers on other phones using BLE to determine when two people encounter each other, and measure for how long they encountered each other and what their proximity was (Die Bundesregierung; https://www.bundesregierung.de/breg-de/themen/corona-warn-app/corona-warn-app-faq-1758392). Features of this app that protect privacy include (1) identifiers are not stored long term and are created from temporary keys that change every 24 h; (2) the names of the user and locations are kept private, especially after 14 days when the random codes are deleted from the smartphone; and (3) if someone becomes infected, they can choose if they want to share their random codes with others, warning them of the possibility of infection (Die Bundesregierung; https://www.bundesregierung.de/breg-de/themen/corona-warn-app/corona-warn-app-faq-1758392).

Initially, the United Kingdom's own contact tracing app was considered deficient and so an attempt was made to adapt Apple's system for use. Apple and Google combined forces to create APIs for mobile devices to use for contact tracing (Mitter 2020; Lazarević 2020). Unfortunately, the United Kingdom said the Apple system could not accurately measure distance well enough for contact tracing (Doffman 2020).

One of the main problems with these contact tracing apps is getting enough people to use them as many countries have made the contact tracing app voluntary. In the United States, only about 12% of the population had contact tracing apps installed on their phone, so the chance that two people had the app installed on their phones that passed each other was only about 1.44% (Newton 2020). It is thought that at least 60% of the population needs to use the app for it to be effective (Lazarević 2020).

In Europe, several contact tracing apps, such as Germany's Corona-Warn-App, Ireland's COVID tracker, and Italy's Immuni, have been linked together to increase usage (Lazarević 2020, 13WOWK; https://www.wowktv.com/news/u-s-world/eu-to-link-national-covid-19-tracing-apps-together/). As of October 2020, these three apps appeared to be the most used apps in the European Union and have been downloaded by about 30 million people, or about two-thirds of all the contact tracing apps that have been downloaded in Europe; unlike in China, the identity of the user is not stored after the contact tracing is completed (13WOWK; https://www.wowktv.com/news/u-s-world/eu-to-link-national-covid-19-tracing-apps-together/, Kamel Boulos and Geraghty 2020).

Privacy concerns have greatly limited the use and effectiveness of contact tracing apps. Privacy seems to be the biggest concern in the EU and the United States as laws have been developed and employed, which require smartphone users to give their consent to use their location for contact tracing (Johnson 2020; Servick 2020). One study found 30 of 50 different apps required the user to give permission for the apps to access various information such as contacts, photos, location data, camera, and more (Sharma and Bashir 2020). Only 16 of the 50 apps stated the user's data would be kept private, anonymous, or encrypted (Sharma and Bashir 2020). This may be partly why contact tracing apps have not been as widespread in the United States. However, states have started to slowly develop their own apps at a slower rate than in many other countries.

With privacy concerns for contact tracing apps, new apps are using non-location GPS-based tracing methods like Bluetooth or WiFi (Lazarević 2020). Many of the contact tracing apps used BLE technology as an alternative to location-based tracking by GPS. Since BLE has limitations often resulting in false positives such as determining when two smartphones are within 2–6 m of each other, especially indoors, and BLE does not effectively penetrate walls or furniture, other sensor technology contact tracing methods have been suggested (Nguyen et al. 2020). A typical smartphone may have 14 or more common sensors that can be used to improve the ability to detect nearby phones more accurately. Some of the sensors that can be used are the barometer, BLE, magnetometer, microphone, and WiFi signal (Nguyen et al. 2020). The microphone was considered a "fine-grained" sensor for appearance sensing and distance measuring, unlike BLE that was not used for distance measuring. When furniture or other barriers reduced the accuracy of BLE, the microphone and WiFi could both be used to increase accuracy from 25% with BLE only systems to about 65% accuracy (Nguyen et al. 2020). Adding these extra sensors is especially important to reduce distance estimate errors indoors.

20.11.2 Apps That Record the Sounds of COVID-19

Medical apps for use on smartphones have become incredibly popular in recent years and can have a big impact on health care (Gupta 2013; Carrion et al. 2016). One sound-related study records daily respiratory sounds from healthy and unhealthy volunteers, on an app installed on their smartphone or on the website (University of Cambridge; https://www.covid-19-sounds.org/en/app/). The University of Cambridge is trying to determine, based on recordings of healthy and unhealthy volunteers, how their coughs and breathing compare to those with COVID-19 and varying other conditions such as asthma (Brown et al. 2020). This will hopefully lead to an alternative or complementary method to direct testing of patients (Brown et al. 2020). By May 22, 2020, their dataset already consisted of several thousand samples and 235 had tested positive for COVID-19. Preliminary results show even a simple binary machine learning classifier can distinguish between healthy subjects and those with COVID-19 (Brown et al. 2020). Results also have shown distinguishing sounds between healthy subjects, those with a cough, those with asthma, and those who have COVID-19 (Brown et al. 2020). Unlike some contact tracing apps, this study will only collect data when you actively fill out your daily survey, which requests your location, your testing status, if you are in the hospital, your symptoms, and multiple recordings of your breathing, coughing, and talking. As of August 2020, they had not yet derived the best system to create a standalone screening tool (Brown et al. 2020).

20.11.3 Drones

A big concern during the pandemic has been the exposure of healthcare professionals or other employees to infected individuals. Drones are versatile tools that can fill multiple roles while keeping users safe from COVID-19 transmission. They can gather remotely sensed images, deliver goods, provide crime surveillance, and even be used in emergency response situations to deliver aid, assess damages, and locate victims (CBInsights; https://www.cbinsights.com/research/drone-impact-society-uav/). Drone technology has been widely employed in this current pandemic as it provides a safe method of data collection and COVID-19 control (Kumar et al. 2020; Preethika et al. 2020). China and India are using drones to safely sanitize and disinfect public areas in a quarter of the time it takes a human to manually spray an area (Kamel Boulos and Geraghty 2020; Kumar et al. 2020; Preethika et al. 2020).

Combining location technologies with drones can allow numerous advantageous applications of drones to help manage the pandemic. By incorporating GIS with drone technology, users can determine where supplies or disinfecting is needed the most (Kamel Boulos and Geraghty 2020). Drones can spray disinfectant from a height of up to 450 ft. without the risk of COVID-19 transmission to employees (Preethika et al. 2020). Drones are also currently being used as safe and fast delivery systems of COVID-19 medical kits, supplies, and personal protective equipment to rural locations in the United States, the United Kingdom, and even China (Kamel Boulos and Geraghty 2020; Cozzens 2020; Kumar et al. 2020). More recently, drones are being used to deliver test kits to people's homes. In a more traditional role, drones can collect aerial images and data such as thermal imaging in temperature detection. This sort of surveillance is also being tested in monitoring respiratory health, and even heart rates of people in indoor and outdoor public areas and patient care facilities (Kumar et al. 2020).

While utilizing drones effectively can decrease COVID-19 transmission, privacy concerns similar to those with smartphone monitoring can be a barrier with such intimate drone surveillance. Proper regulation of where and when drone surveillance should be used is critical for further implementation of this technology in the public sector.

20.11.4 Robots

The use of robots can help reduce exposure to COVID-19 if it limits the social interaction between humans. The pandemic has led to a wide variety of applications for robots to help decrease virus spread. Brain Navi, a Taiwanese firm, created a robot in just 8 weeks that can test potentially infected humans for COVID-19 without putting healthcare professionals at risk (Fig. 20.10) (Brain Navi; https://brainnavi.com/product/nasalswabrobot/). It is based on Brain Navi's NaoTrac neurosurgical navigation robot that has been used in many medical centers in Taiwan (Medgadget; https://www.medgadget.com/2020/08/robotic-clinicians-for-taking-nasal-swabs-during-covid-pandemic.html). The robot uses facial recognition to accurately pinpoint the location of the nostrils for a sample and has a user-friendly interface design structure that only takes 2–5 min to collect a sample (Brain Navi; https://brainnavi.com/product/nasalswabrobot/). The robot spends at least 10 s to collect the sample and patients report that the specimen collected by the robot is more comfortable than if a human collects it. Finally, the collected specimen is placed in a sanitary closed container that is safe for handling (Medgadget; https://

Fig. 20.10 Brain Navi, a Taiwanese firm, created a robot in just 8 weeks that collects a nasal swab sample, from a potentially infected COVID-19 patient, without putting the healthcare worker at risk, in just 2–5 min and then places the sample in a container for safe handling. (This photo was provided by Zoe Lee from Brain Navi with permission)

www.medgadget.com/2020/08/robotic-clinicians-for-taking-nasal-swabs-during-covid-pandemic.html).

Another application of robots is in China where the first "robot-run" restaurant has debuted (Adams 2020). It has a huge menu and can serve up to 600 customers at a time. The robots even cook the food with some menu options ready in as little as 20 s. Food safety standards will be maintained and it is likely, virus transmission rates will be lower than if humans cooked the food.

Another biotechnology company, Koniku, has designed robots that can help "sniff out" COVID-19 infections. They hope to set protein-based sensors onto a silicon chip to smell pathogens and transmit signals to a microcontroller. The goal is to detect the virus quicker than traditional COVID-19 testing methods (Brown 2020). The device, which is smaller than a Frisbee and looks like a UFO, will light up when it detects what it is designed to sniff out (Brown 2020). Eventually, every American may have a robot in their house to detect COVID-19 or other viruses. The company hopes it will be authorized by the U.S. Food and Drug Administration in the first quarter of 2021 (Brown 2020).

20.12 Future Ways to Improve the Analyses

GIS spatial analyses can only effectively guide healthcare professionals with management strategies for the pandemic if they are accurate. It has been considered that "spatial analysis within GIS is the process of building 'models of models'—whereby the outcome of a 'higher level' spatial analysis is dependent upon its data inputs" (Goodchild and Longley 1999). Since many of the pandemic-related maps were constructed quickly, without spending time to validate them, future further analyses could be done on these maps to improve their accuracy. Validation or quality control measures need to be implemented and applied consistently when the general public constructs maps. Map makers will need to double-check their accuracy as maps based on previously made maps can lead to further error (Monmonier 2018).

It has also been a challenge to quickly provide big spatial data to the health industry during the pandemic (Zhou et al. 2020). Creating and expanding upon publicly accessible data repositories like GitHub might facilitate data sharing in near-real-time for future pandemics. Improving access to sub-county data will help with the production of more finite scale analyses, such as including socioeconomic factors (Mollalo et al. 2020). As Internet speeds increase, greater abilities to access big data, will reduce previous epidemiological restrictions of space–time analysis. 5G mobile broadband network technology will be available soon on many mobile phones, which can enable development of more powerful apps in connection with the Cloud (Lin et al. 2016). With the utilization of 5G wireless technology, two people at different ends of the world can communicate at speeds, likely 100 times faster than the typical data rate. Phone memory is expected to increase up to 120 GB, and huge data files can be transferred at a rate of GB's per second, improving our access to big data in the Cloud. Improvements can still be made in using and accessing geospatial big data for GIS developers to create software applications to visualize pandemics, particularly as source restrictions in commercial enterprises may restrict the use of the data for social management, slowing down its quick online visualization (Franch-Pardo et al. 2020; Zhou et al. 2020). Also, greater participation from other countries, besides the United States and China, who created most of the geospatial analyses according to one survey of 63 studies, will lead to greater global surveillance accuracy for future pandemics (Franch-Pardo et al. 2020).

Faster Internet speeds should allow further utilization of mobile technologies and apps, therefore decreasing delays in transferring and receiving disease-related data. Mobile technologies such as contact tracing apps should be utilized more effectively as many developed countries increase usage of mobile technologies. Only 20% of the studies in one review of 63 studies by Franch-Pardo et al. (2020) used information gathered from smartphones. Privacy concerns are important to consider and data protection is important to prevent data breaches and improve the trust of the public to use contact tracing apps or other mobile technologies (Ienca and Vayena 2020). Contact tracing to provide near-real-time statistics and reduction of disease transmission can be greater utilized and privacy concerns addressed.

Some of the smartphone-designed health apps can be improved to lessen privacy concerns and improve their functionality. Even contact tracing apps using BLE have many false positives when measuring the distance between two users (Nguyen et al. 2020). Distance measurement estimates for contact tracing could be improved in the future by using additional smartphone sensors such as air pressure and the magnetic field, along with BLE, microphone, WiFi, or other sensors (Nguyen et al. 2020). Also improving contact tracing technologies to detect when two people are sharing their air space, rather than two people that are close but in separate rooms, is important for future applications (Nguyen et al. 2020).

In addition, the number and usage of self-risk diagnosis and monitoring apps should be increased to reduce the user's exposure of going to a testing center. Many individuals may be afraid to go to a testing center for fear of getting the virus or for reasons of how much the test may cost them. With the creation and further development of many of the apps and technologies that have been discussed, we will have safer methods available to test individuals in their homes so they do not have to expose themselves or others to infection. Other apps, like the Sickweather app (Sickweather; https://www.sickweather.com/), create local maps based on self-reported symptoms of different illnesses, allergies, and more, which can be further augmented to include more data for current viruses like COVID-19. This and similar apps should be further developed to work in combination with public surveillance dashboards or websites such as the Johns Hopkins website to show more localized data. The general public will need to realize there could be a high degree of error for self-reporting apps. The apps can nevertheless serve as a tool to help individuals select stores or towns that have fewer virus cases to conduct their shopping, exercising, or vacationing. More fine-scale spatial GIS applications are needed. Using mobile technologies like cell phones to gather information directly from the user may reduce reporting lags between governmental agencies, health departments, and other reporters that may be delayed for numerous reasons.

Near-real-time case dashboards may have some inaccuracies as they may only include confirmed cases and not self-reported cases (Desjardins et al. 2020). In addition, these dashboards rely on the reporting techniques of different countries/counties/states, which can vary in time and space, and some have even changed their guidelines for how they report cases and deaths. Further, different data sources should all try to update their data consistently at the same time interval. In the future, emerging clusters of COVID-19 cases can be detected by using space–time scan statistics by public health departments to implement on their near-real-time dashboards to achieve improvements in timeliness (Desjardins et al. 2020). To improve the accuracy of near-real-time mapping of cases, it has been suggested that rapid diagnostic antibody tests could be performed at home with the results quickly given uploaded from individual smartphones. Then image processing and machine-learning methods could link to geospatial information to speed up results (Budd et al. 2020). Combining results from different types of tests, incorporating other testing strategies such as sewage monitoring, and adding different socioeconomic risk factors, such as income inequality and median household income, and pre-existing conditions could lead to better disease forecasting (Franch-Pardo et al. 2020; Kanga et al. 2020; Mollalo et al. 2020; Smith and Mennis 2020).

There is room for improvement, as technology advances, to reduce exposure to viruses and create a safer work environment. Collaborative robots, or cobots, could be used in the workplace to help socially distance employees by acting as an intermediary and removing the need for close contact work. They can work alongside humans to help with isolation and provide a big step forward in manufacturing (Bonomi 2020). Greater utilization of drones can also serve to help monitor and manage pandemics as their purpose is only limited by our imagination.

20.13 Conclusions

The explosive production of GIS analyses, timely production of near-real-time dashboards for disease surveillance, and predictive modeling for the COVID-19 pandemic have been incredible. These near-real-time dashboards and other geospatial websites have become popular around the world as healthcare professionals use them to make disease management decisions and citizens use them to monitor the pandemic. While there were previous limitations in GIS software for major epidemiological research, especially in near-real-time surveillance and data storage, these limitations no longer hinder the widespread use of GIS in epidemiology (Musa et al. 2013). Many of these limitations have been resolved by 2020 as geospatial analyses for COVID-19 cases have improved to near-real-time. The accuracy of these GIS analyses can still be improved upon and the accessibility of big spatial data required for these analyses can be expanded with increasing Internet speeds (Ahasan et al. 2020; Field 2020; Franch-Pardo et al. 2020; Zhou et al. 2020). It has been alleged that, during conflict, data and analytics are critical to understanding the changing environment and capabilities often advance quickly (CBS Interactive Inc.; https://static.cbsileads.com/direct/whitepapers/TR_-_Big_data's_role_in_COVID-19_r1.pdf). The constant development of geospatial tools is essential to making informed disease management decisions and to inform the general public about the current status of the pandemic. Their derivation and utilization will be expected now and in the future as COVID-19 has set a new standard for their use.

The effects of the COVID-19 lockdowns, which restricted movement patterns of humans around the globe, have led to a diverse array of environmental geospatial analyses. The effects of the pandemic lockdowns for the most part reduced vehicle collisions with wildlife, reduced noise pollution, reduced air pollution, and improved the Ganga River clarity. The positive environmental impacts of the lockdowns as human activities were restricted may aid decision makers in making informed decisions to decrease our negative influences on the environment.

Other GIS applications and technologies have had a strong impact on managing the pandemic as well. Contact tracing apps and other health-based apps have had some positive impacts on the pandemic and can be greatly improved upon in the future. Privacy of user information is a big concern that has limited the popularity of many of these apps. Drones and robots have quickly been used to combat this global health crisis and decrease everyday exposure to the virus (Musa et al. 2013). Local agencies have adapted quickly to create personalized COVID-19 monitoring procedures and information dissemination methods to work best for their communities; even utilizing pre-built frameworks such as the City of Tempe, in Arizona, that is adapting wastewater monitoring to detect this virus. Where GIS software and spatiotemporal restrictions were formerly thought to be bottlenecks for the field of epidemiology in 2013, new software components such as fog computing and faster Internet speeds have diminished these limitations with near-real-time case monitoring (Musa et al. 2013). Incorporating multiple monitoring strategies will help to create the most accurate disease surveillance visualizations that are possible. As technology continues to advance, the future of geospatial epidemiological analyses will likewise advance.

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