

# An overview of urban analytical approaches to combating the Covid-19 pandemic

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## Introduction

The Covid-19 pandemic has received immeasurable research attention across various scientific fields. We would argue that viewing Covid-19 through the lens of geography and urban analytics plays an essential role in interdisciplinary endeavors to understand and fight the pandemic. First, geographic location and time are the fundamental elements in the spread of infectious diseases, and second, most of the world's population now lives in urban environments. With geospatial technology and data science playing an ever-increasing role in the field, urban analytics is ideally situated at the hub of interdisciplinary research aiming to understand the patterns and dynamics, social impacts, problems, solutions, possible future outcomes, and other cross-disciplinary topics concerning pandemics.

This special issue is the fruit of 2 years of dedicated work starting from the *International Symposium on Geospatial Approaches to Combating Covid-19* held on the 13<sup>th</sup>–14<sup>th</sup> of December 2021 in Florence, Italy, as a pre-International Cartographic Conference symposium. This hybrid event facilitated in-person and virtual participation. The symposium served as a research forum during the early stages of the pandemic when scientists and practitioners had been making enormous research efforts to combat the Covid-19 pandemic. Following the standard peer review process, this special issue includes papers studying various aspects of the pandemic that were further developed from the work presented at the symposium while others were received after an open call for submissions published on the journal's website.

To situate the special issue in context, this editorial provides an overview of the literature on Covid-19 through the lens of urban analytics. We are particularly interested in the following questions: 1) What research themes have appeared in the literature? 2) What can be learned from the current research? 3) Where are the gaps and future research opportunities for urban analytics in combating epidemic outbreaks? Informed by current published work, this editorial examines research themes at the intersection of urban analytics and Covid-19. First, we identify the main research themes in the literature on urban analytics and epidemic outbreaks. This is followed by summarizing key findings and insights gained from the current research. We conclude by discussing the unique importance, gaps, and opportunities for urban analytical approaches to contribute significantly to future cross-disciplinary research endeavors against epidemics.

## Current themes

To have an evidence-based understanding of the current threads of geospatial research on Covid-19, we first conducted a literature survey of published research since the outbreak of the pandemic. The

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survey identified a collection of peer-reviewed journal articles published between 2020 and early 2023 based on keyword searches on “Covid-19” or “coronavirus” or “Covid” and “geospatial” or “geographic” and “Urban” or “City” or “cities” or “metropolitan” and “analysis” or “modeling.” The search was performed in more than 10 bibliography databases, including Web of Science, ScienceDirect, Medline, Academic Search Complete, Directory of Open Access Journals, and others. We examined the search result of 1885 articles in WordStat, a content analysis and text mining software. Based on the meta-analysis of the titles and keywords of these articles, [Table 1](#) summarizes the major research themes and techniques in geospatial and urban analytical studies of Covid-19 in the past 3 years. Some commonly used techniques and a few selected articles as example references are listed in the table for each research thread.

The urban analytical research approach has contributed to a broad spectrum of research themes and topics related to the pandemic. [Figure 1](#) presents a framework of the interactions between the evolution of the pandemic and human dynamics, urban systems, healthcare services, health policy, and management systems. Prior studies have found that pandemic waves are first and foremost modulated by the Covid-19 virus variants and medical advances (e.g., [Yang et al., 2023](#)). The alpha, delta, and omicron variants demonstrated significantly different infectiousness, eventually leading to drastically different transmissibility and mortality rates. This is represented in the center of the [Figure 1](#). In addition, the availability of vaccines has made a profound difference in the spread of the pandemic. Research theme T1 examines the pandemic curves and spreading patterns, particularly space-time clusters, of incidences and transmission or mortality rates. In [Figure 1](#), the three component modules around the pandemic interconnect with each other, each representing one aspect of the human-environment systems interacting directly with the pandemic. The pandemic curves and patterns impact, and are also significantly influenced by, changes in the three components. This is seen in the literature that addresses research issues arising from the interactions between each component and the pandemic dynamics. As shown in the figure, several research themes from [Table 1](#) may be applicable in respective components and thus help us better understand the pandemic.

## Observations and discussions

Some general trends are observed from the review of the current themes emerging from the literature survey on Covid-19. These trends range from diverse data sources, explorations of human mobility, to understanding the risk factors, social impacts, human responses to Covid-19, and disease mapping over space and time.

### *Extensive range of data sources*

As one might expect in today’s world, our survey of the literature found substantially expanded data sources for studying Covid-19, compared with past historical epidemics. The amount and data types have increased significantly from surveillance and monitoring to that derived from synthetic data for analyzing and modeling Covid-19. Our survey found the following general data sources in urban analytical Covid-19 research:

- **Live registry data.** Near real-time registry data have been made available by government and public health agencies at various administrative levels. Such data have been widely disseminated via reports and dashboards to inform the public, researchers, and practitioners (e.g., [Caraballo et al., 2020](#); [Schwartz et al., 2023](#)).
- **Local reports.** Researchers also obtained data from local online sources through web scraping systems. Geographically identifiable online reports have provided valuable local

**Table 1.** Covid-19 research themes and topics through the lens of geography and urban analytics.

Research themes	Selected topics	Selected techniques	Selected articles
<b>T1. Pandemic trends, patterns, and information dissemination</b>	Transmission modeling, cross-sectional or spatiotemporal patterns analysis, visual dissemination of information	GIS, spatial clustering, spatiotemporal clustering, machine learning, Bayesian methods, cross-sectional studies, spatial epidemiology modeling, dashboards, web-based GIS, visual analytics	<a href="#">Kan et al., 2021</a> ; <a href="#">Nazia et al., 2022</a> ; <a href="#">Yang et al., 2023</a> ; <a href="#">Yu &amp; Liu 2023</a> ; <a href="#">Praharaj et al., 2023</a> ; <a href="#">Atek et al., 2022</a> .
<b>T2. Health surveillance and contact tracing</b>	Live registry, contact tracing, human mobility	GIS, Crowd-sourced data (e.g., social media), machine learning methods, GPS, qualitative surveys, phylogeographic analysis, disease mapping	<a href="#">Jia et al., 2020</a> ; <a href="#">Elgazzar et al., 2021</a> ; <a href="#">Kan et al., 2021</a> ; <a href="#">Schwarz et al., 2023</a> .
<b>T3. Assessing risk factors</b>	Socioeconomic factors, geographical factors, demographic factors, environmental factors, human behavioral factors	Multivariate statistical analysis, spatial regression, spatial data mining, machine learning, geospatial network analysis	<a href="#">Hamidi et al., 2020</a> ; <a href="#">Millett et al., 2020</a> ; <a href="#">Chang et al., 2021</a> ; <a href="#">Yang et al., 2023</a> ; <a href="#">Yu &amp; Liu 2023</a> ; <a href="#">Venerandi et al., 2023</a> .
<b>T4. Healthcare services</b>	Healthcare accessibility, demand-supply analysis of service coverage, vaccine coverage, site selection, urban–rural disparities	GIS, network analysis, accessibility analysis, location-allocation modeling, Kernel density estimation, multicriteria evaluation, analytic hierarchy process	<a href="#">Rader et al., 2020</a> ; <a href="#">Mohammadi et al., 2021</a> .
<b>T5. Health policy intervention and management</b>	Evaluation of intervention policy. Vaccine coverage and efficacy	Geosimulation and agent-based modeling, epidemiology models, multivariate statistics	<a href="#">Zhang et al., 2021</a> ; <a href="#">Wallace et al., 2022</a> ; <a href="#">Li et al., 2023</a> ; <a href="#">Szanyi et al., 2023</a> ; <a href="#">Tran et al., 2023</a> .
<b>T6. Social impacts and responses</b>	Social, economic, or environmental impacts, social vulnerability, mental health; housing, urban air quality, recreational activities	Social media analytics, natural language processing, spatial statistics, emerging hot spot analysis, ecological analysis, machine learning, network analysis, Bayesian hierarchical modeling, visual analytics	<a href="#">Tiwari et al., 2021</a> ; <a href="#">Gimbrone et al., 2021</a> ; <a href="#">Huang et al., 2022</a> ; <a href="#">Thakur 2022</a> ; <a href="#">Wallace et al., 2022</a> ; <a href="#">Tran et al., 2023</a> ; <a href="#">Angel et al., 2023</a> ; <a href="#">Wolday &amp; Bocker 2023</a> .
	Human mobility		<a href="#">Lai et al., 2020</a> ; <a href="#">Xin et al., 2022</a> ; <a href="#">Zhang et al., 2023</a> ; <a href="#">Tong et al. 2023</a> .
	Health disparities		<a href="#">Li &amp; Huang 2023</a> ; <a href="#">Dass et al., 2023</a> ; <a href="#">Li et al., 2023</a> ; <a href="#">Arango-Londoño et al., 2023</a> .

*(continued)*

Table I. (continued)

Research themes	Selected topics	Selected techniques	Selected articles
<b>T7. Prediction</b>	Spatio-temporal prediction of the pandemic evolution	Registry data and crowd-sourced data analytics, machine learning, GeoAI.	Chang et al., 2021; Atek et al., 2022; Yang et al., 2023; Tong et al. 2023.

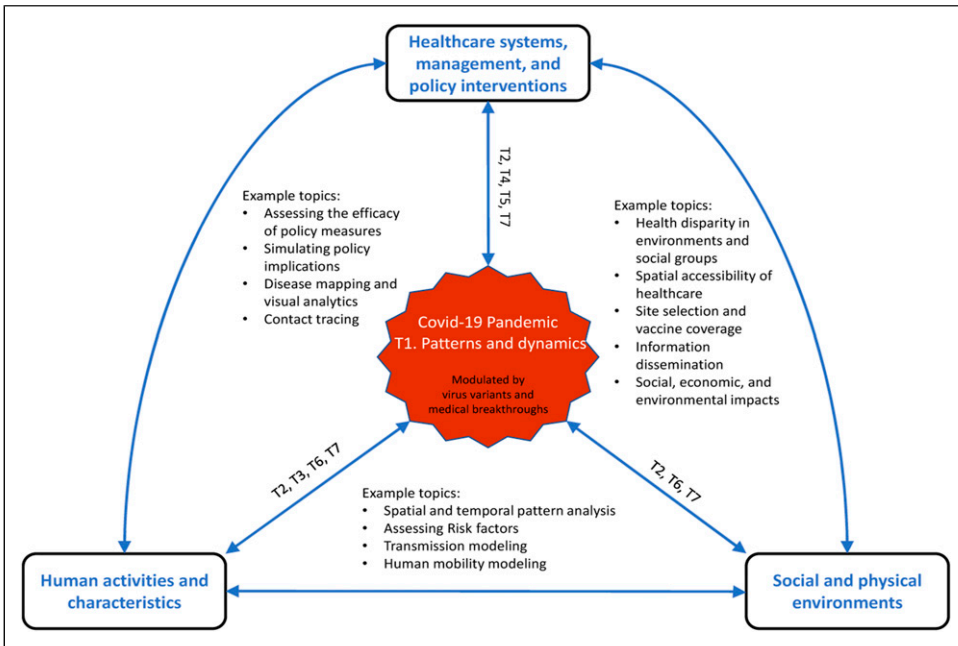


Figure 1. A framework of the Covid-19 pandemic dynamics in urban systems.

data and can be seen as a favorable supplementary source to the standard registry data (e.g., Kan et al., 2021; Praharaj et al., 2023).

- **Social media data.** Social media posts from Twitter, Weibo, and other popular platforms have been used in many studies as social sensing sources, often powered by natural language processing and text mining techniques. Researchers have used social media analytics to detect mental health problems, social responses to health intervention policies, needs for healthcare services, and other hidden or manifested public health issues to study the social impact of the pandemic (e.g., Tiwari et al., 2021; Huang et al., 2022; Tran et al., 2023).
- **Location intelligence data and aggregated trends data.** In the worldwide efforts to fight the pandemic, many companies made their resources open and freely available for research and education. Examples include SafeGraph’s points of interest (POI) and mobility data, Google Trends data, and Weibo Mobility Index data. Such open data have been widely used in studies of the pandemic (e.g., Lai et al., 2020; Chang et al., 2021).
- **GPS-enabled mobile device data.** Studies have also collected space-time trajectory data from mobile devices for surveillance and contact tracing (e.g., Jia et al., 2020; Gimbrone

et al., 2021). Due to privacy concerns, collecting individual data is atypical and primarily only seen in local-scale research projects with human subject consent and special restrictions.

- **Internet of Things and sensor network data.** With more smart city technologies being adopted in many cities, human and object dynamics can be learned from data of all sorts of intelligent devices by the Internet of Things (IoT) technology and wireless sensor network (e.g., Hu et al., 2021). For instance, prior studies used bike-sharing data (Xin et al., 2022) to monitor human mobility changes during the pandemic.
- **Others.** Other types of data, such as social network data (e.g., Huang et al., 2022), remote sensing data (e.g., Atek et al., 2022), Covid-19 policy packages (e.g., Szanyi et al., 2023), and even synthetic data (e.g., Wallace et al., 2022) have also been used for monitoring, contact tracing, pattern identification, or prediction purposes.

*Human mobility.* Human mobility studies have also received wide attention in the literature during Covid-19. This comes as little surprise because human mobility is closely related to effective contact rates between people, which is the first of the three essential factors in infectious disease transmissibility, including the effective contact rate, the infectious period of the virus, and the likelihood of infection per contact. Due to the critical role of human dynamics in the virus-spreading process, the factor of human mobility spans multiple research themes illustrated in Figure 1. On the theme of human activities, changes in human mobility are used as one of the geographical contextual factors to characterize shifts in human activity patterns in an urban area, which subsequently influence the transmissibility rate in that area (e.g., Yang et al., 2023). Significant mobility changes have been found in the United States and other parts of the world since the onset of the pandemic, and the changes have varied among urban and rural counties (e.g., Lai et al., 2020).

Regarding public health services, human mobility and geographical accessibility are the most common topics of investigation. During the pandemic, the demand and supply of public health services were constantly in flux. Spatial accessibility analyses and location-allocation modeling have been shown to identify gaps and evaluate possible solutions effectively. For instance, the spatial coverage of accessible vaccination sites was a major concern when there was a shortage of vaccines and optimal locations of new sites were to be selected (e.g., Mohammadi et al., 2021). The factor of human mobility is also seen in studies of health policy assessment. Several intervention policies attempt to constrain human interactions, such as the lockdown policy, curfew, quarantine, and so on. Urban analytical methods were adopted to evaluate the efficacy of intervention strategies such as home isolation, contact tracing, temperature screening in public areas, vaccination, and others (e.g., Zhang et al., 2021).

### *Understanding risk factors, social impacts, and human responses*

An important theme in spatial epidemiology is to analyze the effects of risk factors in the dynamics of the pandemic. The literature has seen broad interest in understanding the impacts of socio-economic factors such as income (e.g., Li and Huang 2023; Arango-Londoño et al., 2023), geographical factors such as urban and rural areas (e.g., Lai et al., 2020), demographic factors such as age and race (e.g., Adepoju et al., 2022), environmental factors such as air quality (e.g., Nottmeyer et al., 2023), and cultural and educational factors such as handwashing habits and attitudes about vaccination (Benham et al., 2021). Crowd-sourced and open data have been excellent sources for understanding these impacts and human responses. Common urban analytical techniques in these studies include geospatial analysis and mapping, spatial regression, network analysis, spatial data mining and machine learning, textual analytics, semantic analysis, multidimensional scaling, multicriteria decision analysis, and others (e.g., Hamidi et al., 2020; Chang et al., 2021; Yang et al., 2023; Dass et al., 2023; Li et al., 2023; Yu and Liu 2023; Venerandi et al., 2023).

A large body of work has also focused on the pandemic's profound impact on human life and people's responses to such impact. Researchers have found significant effects of Covid-19 on people's life choices, such as housing preferences (Wolday & Bocker 2023) and recreational park visiting preferences (Huang et al., 2022). Many studies also aimed to find practical solutions to the impact. Urban analytical techniques have been used to find effective strategies in response to the gigantic pressure on the limited capacity of some urban infrastructures, such as the healthcare system (Boyacı and Şişman 2022) and waste treatment facilities (Thakur 2022) during the peak periods of the pandemic waves. In this special issue, Zhang et al. (2023) used social media analytics and spatial analyses to investigate the effectiveness of transit agencies' communication via Twitter with riders about service content and essential Covid-19 health prevention policy requirements. Tong et al. (2023) developed a spatiotemporal model to assist travel route planning for the least exposure risk in an urban environment.

### *Spatiotemporal patterns and disease mapping*

The spread of the virus in space and time is one of the primary research issues addressed by many studies. Researchers have used geospatial and analytical techniques to analyze the patterns of Covid-19 incidence, mortality, transmission rates, or other metrics describing the disease burden (e.g., Xin et al., 2022). Some cross-sectional studies investigated the spatial patterns in cities and compared differences among regions in the world. In contrast, some other studies have investigated the temporal dynamics and monitored the spatiotemporal evolution of the spread (e.g., McCrone et al., 2022; Yang et al., 2023). Geospatial and urban analytical techniques such as space-time clustering techniques (e.g., Kan et al., 2021; Jiang and De Rijke 2021), social media analytics, and GeoAI (Atek et al., 2022) have been instrumental in these research efforts.

Disease mapping, particularly web-based dashboards, has been the most influential way to communicate the dynamics of the pandemic. Numerous dashboards and other web-based systems have been developed at local, regional, country, and global scales (e.g., Praharaaj et al., 2023). Disease mapping provides geographic illustrations of spatial or spatiotemporal patterns. Most web-based Covid-19 dashboards disseminate and update pandemic information to the public promptly. In addition, some specially developed interactive systems visualize the spatiotemporal changes of the pandemic measures and integrate selected geographic context factors to support visual exploration and analytical reasoning of potential associations between the context factors and the pandemic dynamics (e.g., Praharaaj et al., 2023).

### **Challenges and future opportunities**

As might be gathered from this editorial, there has been an abundance of studies about the Covid-19 pandemic and its impacts on the world, particularly in cities. The urban analytical approach is indispensable in understanding, analyzing, and combating an epidemic outbreak in urban environments. Despite the considerable success, this approach faces several challenges awaiting future research endeavors. Meanwhile, with breakthroughs in big data research and artificial intelligence, along with other advances in health geography, there are great opportunities for geospatial and urban analytical approaches to contribute to epidemic research more significantly. Discussed below are some research avenues.

#### *Prediction*

More research is needed for the prediction of pandemic dynamics. For instance, forecasts of transmissibility, cases, deaths, and hospitalizations can help inform public health decisions and

develop appropriate response strategies. There are short-term, mid-term, and long-term predictions depending on the time horizon. Short-term predictions of the next few days or weeks were chosen in most Covid-19 prediction efforts (e.g., Yang et al., 2023; Tong et al., 2023). Some government-led research centers have set research priorities on prediction. For example, the Center for Disease Control (CDC) in the United States has established a forecast hub that maintains multiple weekly forecasts of the nation's Covid-19 hospitalization, cases, and deaths (<https://covid19forecasthub.org/>). The dynamically updated website visualizes predictions up to 4 weeks in the future. Currently, the website acknowledges that most of these forecasts have failed to predict rapid changes in trends reliably. Future research efforts are in great demand to improve accuracy. Predictions of the future dynamics of a pandemic often suffer from low prediction accuracy. Various reasons may be at work. First, prediction models are mostly generated from past data and/or knowledge, while many dynamically changing factors are at play for future scenarios. Some factors are easier to observe and model, while others are less predictable. For instance, the emergence of new virus variants or sudden impactful events can cause significant changes in transmissibility, hospitalization, and mortality rates. Second, current predictions are made at highly aggregated levels for national or global forecasts. These high-level predictions have limited capability to inform local decision-making. Future predictions should be made for local places and for longer time horizons. Third, research attention should be paid to integrating data-driven and knowledge-based approaches (e.g., those relying on domain knowledge in epidemiology) to improve the models' predictive accuracy and explainability. Although challenging, the steady technical advances in geospatial technology, machine learning and artificial intelligence, bioinformatics, and supercomputing power provide excellent opportunities for significant improvements in future prediction models.

### *Contact tracing and alert systems*

Suitable implementations of contact tracing and alert systems are seen in some cities or regions but are not widely available. Jia et al. (2020) used a large volume of mobile phone data from individuals leaving or transiting through Wuhan at the onset of the Covid-19 to analyze the population flow and related spread of the virus. The Hong Kong Center for Health Protection provided contact tracing records of building level location data for confirmed cases (Kan et al., 2021). People's mobility trajectories can be used for contact tracing, but such data cannot be publicly available due to privacy protection. There are huge social and ethical hurdles for releasing individual level location data in most parts of the world. Therefore, researchers have been using urban analytical techniques to detect contacts from heterogeneous data sources in the public domain, such as geotagged social media data, location-based services data, surveillance photos and videos, aggregated mobility reports, flight information, and others (e.g., McCrone et al., 2022). Future research is needed in methodological developments for contact tracing techniques and also in social and legal aspects of the issue. The disparity problem might also appear due to unequal availability of data, inequality in access to mobile devices and knowledge to use them, different perceptions of privacy concerns, and so on.

### *Geographically contextualized analysis and modeling*

Researchers have investigated a wide range of risk factors; however, a better understanding of the impact of the factors and the relationships could help people respond to and combat epidemics more effectively. Risk factors are found and analyzed from many perspectives. Whether or how they interact with each other and multiply the effects will need to be further explored. Most, if not all, of the factors, are situated in a geographic context. Thus, a geographically contextualized analysis approach is an excellent way to integrate these risk factors so that the contextualized synergetic effects of risk factors can be examined.

The past years have seen significant achievements in cross-disciplinary geospatial and urban analytical research to combat the Covid-19 pandemic. New methods and tools have been developed. Geospatial and urban analytic perspectives are proven to be of utmost importance and are irreplaceable. Location data, geographic thinking, and urban analytical techniques play significant roles in these studies. With the ever-increasing volume of spatial big data and location intelligence, as well as the rapidly growing GeoAI techniques, urban analytics has boundless opportunities to contribute significantly to future cross-disciplinary research endeavors against epidemics.

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### **References**

- Adepoju OE, Chae M, Liaw Wet al. (2022) Transition to telemedicine and its impact on missed appointments in community-based clinics. *Annals of Medicine* 54(1): 98–107. DOI: [10.1080/07853890.2021.2019826](https://doi.org/10.1080/07853890.2021.2019826)
- Angel A, Cohen A, Dalyot S, et al. (2023) Impact of COVID-19 policies on pedestrian traffic and walking patterns. *Environment and Planning B: Urban Analytics and City Science*. 50(5): 1178–1193.
- Arango-Londoño D, Ortega-Lenis D, Moraga P, et al. (2023) Spatial modeling and socioeconomic inequities of COVID-19 in the urban area of the city of Cali, Colombia. *Spatial and Spatio-Temporal Epidemiology* 44: 100561. DOI: [10.1016/J.SSTE.2022.100561](https://doi.org/10.1016/J.SSTE.2022.100561)
- Atek S, Pesaresi C, Eugeni M, et al. (2022) A Geospatial Artificial Intelligence and satellite-based earth observation cognitive system in response to COVID-19. *Acta Astronautica* 197: 323–335. DOI: [10.1016/j.actaastro.2022.05.013](https://doi.org/10.1016/j.actaastro.2022.05.013)



- Benham JL, Lang R, Kovcs Burns K, et al. (2021) Attitudes, current behaviours and barriers to public health measures that reduce COVID-19 transmission: a qualitative study to inform public health messaging. *PLoS ONE* 16(2): 1–14. DOI: [10.1371/journal.pone.0246941](https://doi.org/10.1371/journal.pone.0246941)
- Boyacı AÇ and Şişman A (2022) Pandemic hospital site selection: a GIS-based MCDM approach employing Pythagorean fuzzy sets. *Environmental Science and Pollution Research International* 29: 1985–1997. DOI: [10.1007/s11356-021-15703-7](https://doi.org/10.1007/s11356-021-15703-7)
- Caraballo C, McCullough M, Fuery MA, et al. (2020) COVID-19 infections and outcomes in a live registry of heart failure patients across an integrated health care system. *PLoS ONE* 15(9): e0238829. DOI: [10.1007/s11356-021-15703-7](https://doi.org/10.1007/s11356-021-15703-7)
- Chang S, Pierson E, Koh PW, et al. (2021) Mobility network models of COVID-19 explain inequities and inform reopening. *Nature* 589: 82–87. DOI: [10.1038/s41586-020-2923-3](https://doi.org/10.1038/s41586-020-2923-3)
- Dass S, O'Brien DT and Ristea A (2023) Strategies and inequities in balancing recreation and COVID exposure when visiting green spaces. *Environment and Planning B: Urban Analytics and City Science*. 50(5): 1161–1177.
- Elgazzar H, Spurlock K and Bogart T (2021) Evolutionary clustering and community detection algorithms for social media health surveillance. *Machine Learning with Applications* 6: 100084. DOI: [10.1016/j.mlwa.2021.100084](https://doi.org/10.1016/j.mlwa.2021.100084)
- Gimbrone C, Rutherford C, Kandula S, et al. (2021) Associations between COVID-19 mobility restrictions and economic, mental health, and suicide-related concerns in the US using cellular phone GPS and Google search volume data. *PLoS ONE* 16(12): e0260931. DOI: [10.1371/journal.pone.0260931](https://doi.org/10.1371/journal.pone.0260931)
- Hamidi S, Sabouri S and Ewing R (2020) Does density aggravate the COVID-19 pandemic? Early findings and lessons for planners. *Journal of the American Planning Association* 86(4): 495–509. DOI: [10.1080/01944363.2020.1777891](https://doi.org/10.1080/01944363.2020.1777891)
- Hu X, Ngai EC, Castellano G, et al. (2021) Special issue on ‘toward intelligent internet of medical things and its COVID-19 applications and beyond. *IEEE Internet of Things Journal* 8(21): 15649–15651. DOI: [10.1109/JIOT.2021.3114575](https://doi.org/10.1109/JIOT.2021.3114575)
- Huang JH, Floyd MF, Tateosian LG, et al. (2022) Exploring public values through Twitter data associated with urban parks pre- and post-COVID-19. *Landscape and Urban Planning* 227: 104517. DOI: [10.1016/j.landurbplan.2022.104517](https://doi.org/10.1016/j.landurbplan.2022.104517)
- Jia JS, Lu X, Yuan Y, et al. (2020) Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 582(7812): 389–394. DOI: [10.1038/s41586-020-2284-y](https://doi.org/10.1038/s41586-020-2284-y)
- Jiang B and de Rijke CA (2021) A power-law-based approach to mapping COVID-19 cases in the United States. *Geo-spatial Information Science* 24(3): 333–339. DOI: [10.1080/10095020.2020.1871306](https://doi.org/10.1080/10095020.2020.1871306)
- Kan Z, Kwan M, Huang J, et al. (2021) Comparing the space-time patterns of high-risk areas in different waves of COVID-19 in Hong Kong. *Transactions in GIS* 25(6): 2982–3001. DOI: [10.1111/tgis.12800](https://doi.org/10.1111/tgis.12800)
- Lai Y, Charpignon ML, Ebner DK, et al. (2020) Unsupervised learning for county-level typological classification for COVID-19 research. *Intelligence-Based Medicine* 1: 100002. DOI: [10.1016/j.ibmed.2020.100002](https://doi.org/10.1016/j.ibmed.2020.100002)
- Li R and Huang Y (2023) COVID-19 pandemic and minority health disparities in New York City: a spatial and temporal perspective. *Environment and Planning B: Urban Analytics and City Science*. 50(5): 1194–1211.
- Li Y, Ran Z, Tsai Let al. (2023) Using CDR (Call Detail Records) to determine mobility patterns of different socio-demographic groups in the western area of Sierra Leone during early COVID-19 crisis. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1298–1312.
- McCrone JT, Hill V, Bajaj S, et al. (2022) Context-specific emergence and growth of the SARS-CoV-2 Delta variant. *Nature* 610: 154–160. DOI: [10.1038/s41586-022-05200-3](https://doi.org/10.1038/s41586-022-05200-3)
- Millett GA, Jones AT, Benkeser D, et al. (2020) Assessing differential impacts of COVID-19 on black communities. *Annals of Epidemiology* 47: 37–44. DOI: [10.1016/j.annepidem.2020.05.003](https://doi.org/10.1016/j.annepidem.2020.05.003)
- Mohammadi A, Mollalo A, Bergquist R, et al. (2021) Measuring COVID-19 vaccination coverage: an enhanced age-adjusted two-step floating catchment area model. *Infectious Diseases of Poverty* 10: 118. DOI: [10.1186/s40249-021-00904-6](https://doi.org/10.1186/s40249-021-00904-6)

- Nazia N, Butt ZA, Bedard ML, et al. (2022) Methods used in the spatial and spatiotemporal analysis of COVID-19 epidemiology: a systematic review. *International Journal of Environmental Research and Public Health* 19(14): 8267. DOI: [10.3390/ijerph19148267](https://doi.org/10.3390/ijerph19148267)
- Nottmeyer L, Armstrong B, Lowe R, et al. (2022) The association of COVID-19 incidence with temperature, humidity, and UV radiation – A global multi-city analysis. *The Science of the Total Environment* 854: 158636. DOI: [10.1016/j.scitotenv.2022.158636](https://doi.org/10.1016/j.scitotenv.2022.158636)
- Praharaj S, Solis P and Wentz EA (2023) Deploying geospatial visualization dashboards to combat the socio-economic impacts of COVID-19. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1262–1279.
- Rader B, Astley CM, Sy KTL, et al. (2020) Geographic access to United States SARS-CoV-2 testing sites highlights healthcare disparities and may bias transmission estimates. *Journal of Travel Medicine* 27(7): taaa076. DOI: [10.1093/jtm/taaa076](https://doi.org/10.1093/jtm/taaa076)
- Schwartz DL, Stewart A, Harris L, et al. (2023) The Memphis Pandemic Health Informatics System (MEMPHI-SYS)—Creating a metropolitan COVID-19 data registry linked directly to community testing to enhance population health surveillance. *Disaster Medicine and Public Health Preparedness* 17: E326. DOI: [10.1017/dmp.2022.284](https://doi.org/10.1017/dmp.2022.284)
- Szanyi J, Wilson T, Howe S, et al. (2023) Epidemiologic and economic modelling of optimal COVID-19 policy: public health and social measures, masks and vaccines in Victoria, Australia. *The Lancet Regional Health. Western Pacific* 32: 100675. DOI: [10.1016/J.LANWPC.2022.100675](https://doi.org/10.1016/J.LANWPC.2022.100675)
- Tran M, Draeger C, Wang X, et al. (2023) Monitoring the well-being of vulnerable transit riders using machine learning based sentiment analysis and social media: lessons from COVID-19. *Environment and Planning B: Urban Analytics and City Science* 50(1): 60–75. DOI: [10.1177/23998083221104489](https://doi.org/10.1177/23998083221104489)
- Thakur DV (2022) Locating temporary waste treatment facilities in the cities to handle the explosive growth of HCWs during pandemics: a novel Grey-AHP-OCRA hybrid approach. *Sustainable Cities and Society* 82: 103907. DOI: [10.1016/j.scs.2022.103907](https://doi.org/10.1016/j.scs.2022.103907)
- Tiwari A, Dadhania AV, Ragunathrao VAB, et al. (2021) Using machine learning to develop a novel COVID-19 vulnerability index (C19VI). *The Science of the Total Environment* 773: 145650. DOI: [10.1016/j.scitotenv.2021.145650](https://doi.org/10.1016/j.scitotenv.2021.145650)
- Tong C, Shi W, Zhang A, et al. (2023) Predicting onset risk of COVID-19 symptom to support healthy travel route planning in the new normal of long-term coexistence with SARS-CoV-2. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1212–1227.
- Venerandi A, Aiello LM and Porta S (2023) Urban form and COVID-19 cases and deaths in greater London: an Urban morphometric approach. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1228–1243.
- Wallace R, Franklin R, Grant-Muller S, et al. (2022) Estimating the social and spatial impacts of Covid mitigation strategies in United Kingdom regions: synthetic data and dashboards. *Cambridge Journal of Regions, Economy and Society* 15(3): 683–702. DOI: [10.1093/cjres/rsac019](https://doi.org/10.1093/cjres/rsac019)
- Wolday F and Bocker L (2023) Exploring changes in residential preference during COVID-19. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1280–1297.
- Xin R, Ai T, Ding L, et al. (2022) Impact of the COVID-19 pandemic on urban human mobility - A multiscale geospatial network analysis using New York bike-sharing data. *Cities* 126: 103677. DOI: [10.1016/2Fj.cities.2022.103677](https://doi.org/10.1016/2Fj.cities.2022.103677)
- Yang H, Yao XA, Liu R, et al. (2023) Developing a place-time-specific index to measure and examine the spatiotemporally varying transmissibility of COVID-19. *Annals of the American Association of Geographers*. Published online. DOI: [10.1080/24694452.2023.2182758](https://doi.org/10.1080/24694452.2023.2182758)
- Yu Z and Liu X (2023) Spatial variations of the third and fourth Covid-19 waves in Hong Kong: a comparative study using built environment and socio-demographic characteristics. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1144–1160.

- 
- Zhang N, Jack Chan P-T, Jia W, et al. (2021) Analysis of efficacy of intervention strategies for COVID-19 transmission: a case study of Hong Kong. *Environment International* 156: 106723. DOI: [10.1016/j.envint.2021.106723](https://doi.org/10.1016/j.envint.2021.106723)
- Zhang W, Barchers C and Smith-Colin J (2023) Transit communication via Twitter during the COVID-19 pandemic. *Environment and Planning B: Urban Analytics and City Science* 50(5): 1244–1261.