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REVIEW ARTICLE

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A review of GIS methodologies to analyze the dynamics of COVID-19 in the second half of 2020

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Abstract

COVID-19 has infected over 163 million people and has resulted in over 3.9 million deaths. Regarding the tools and strategies to research the ongoing pandemic, spatial analysis has been increasingly utilized to study the impacts of COVID-19. This article provides a review of 221 scientific articles that used spatial science to study the pandemic published from June 2020 to December 2020. The main objectives are: to identify the tools and techniques used by the authors; to review the subjects addressed and their disciplines; and to classify the studies based on their applications. This contribution will facilitate comparisons with the body of work published during the first half of 2020, revealing the evolution of the COVID-19 phenomenon through the lens of spatial analysis. Our results show that there was an increase in the use of both spatial statistical tools (e.g., geographically weighted regression, Bayesian models, spatial regression) applied to socio-economic variables and analysis at finer spatial and temporal scales. We found an increase in remote sensing approaches, which are now widely applied in studies around the world. Lockdowns and associated changes in human mobility have been extensively examined using spatiotemporal techniques. Another dominant topic studied has been the relationship between pollution and COVID-19 dynamics, which enhance the impact of human activities on the pandemic's evolution. This represents a shift from the first half of 2020, when the research focused on climatic and weather factors. Overall, we have seen a vast increase in spatial tools and techniques to study COVID-19 transmission and the associated risk factors.

1 | INTRODUCTION

Since early 2020, the COVID-19 pandemic has been a substantial threat to public health worldwide. COVID-19 is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2; Shi, Chen, Fan, & Chen, 2020). The pandemic is believed to have started at a seafood market in Wuhan, Hubei Province, China. The virus quickly spread to other countries in eastern Asia, Europe, and the remainder of the world (Spagnuolo, De Vito, Rengo, & Tatullo, 2020). The spread of the pandemic has been widely studied, and the strategies and tools applied to research the spatial and temporal changes in COVID-19 transmission have been diverse and evolved quickly to adapt to the data available and knowledge of the disease. Since the start of the pandemic, over 163 million individuals have been infected and over 3.3 million have died. The duration of the pandemic, along with the huge impacts on societies, economies, politics, and public health, has greatly influenced spatial analysis' role in understanding COVID-19.

The spatial tools and techniques used to understand COVID-19 have been diverse, and a review of the current knowledge can help researchers to develop and refine methodologies adopted to influence decision-making, public health guidelines, and the allocation of resources such as vaccines and tests (Bernasconi & Grandi, 2021; Cordes & Castro, 2020; Melin, Monica, Sanchez, & Castillo, 2020; Vaz, 2021). A review of the methodologies used can contribute to improve COVID and post-COVID management and plan for future pandemics.

In the first half of 2020, we had far less information about COVID-19, due to logistics, the novelty of the disease, and lack of research and data. As the year progressed, we saw a very substantial increase in the number of studies related to the pandemic, especially those that utilize spatial analysis. In this regard, based on what was published in the first half of 2020 (January–May 2020), Franch-Pardo, Napoletano, Rosete-Verges, and Billa (2020) identified 63 works that applied geographic information systems (GIS) and spatial science to analyze COVID-19, grouping the studies into five main topics: spatiotemporal analysis, health and social geography, environmental variables, data mining, and web-based mapping. Inspired by previous work (Ahasan, Alam, Chakraborty, & Hossain, 2020; Boulos & Geraghty, 2020; Koller, Wohlrab, Sedlmeir, & Augustin, 2020; Sarfo & Karuppannan, 2020; Smith & Mennis, 2020; Yang et al., 2020; Zhou et al., 2020), we now provide an updated systematic review of studies published in the second half of 2020.

This will tell us about the thematic evolution of GIS and spatial analysis used in COVID-19 studies compared with the first half of 2020. As we mentioned, during the first months of the pandemic, remarkable reviews or reflections on the usefulness of these technologies and approaches for pandemic research were published (Casti, 2020; Collectif, 2020; Dangermond, De Vito, & Pesaresi, 2020; Devasia, Lakshminarayanan, & Kar, 2020; Klapka, Ellegård, & Frantál, 2020; Méndez, 2020; Radojević, Lazić, & Cimbaljević, 2020; Rosenkrantz, Schuurman, Bell, & Amram, 2020; Wolf, 2020; Zúñiga, Pueyo, & Postigo, 2020). Our goal is to provide another valuable resource for researchers applying GIS and spatial analysis to study COVID-19.

2 | MATERIAL AND METHODS

This research is based on the systematic review conducted by Franch-Pardo et al. (2020) and goes further with the analysis of new research findings. Based on the spatial analysis methodologies and tools identified in the GIS reviews of the first half of 2020 (Ahasan et al., 2020; Boulos & Geraghty, 2020; Franch-Pardo et al., 2020; Koller et al., 2020; Sarfo & Karuppannan, 2020; Smith & Mennis, 2020; Yang et al., 2020; Zhou et al., 2020), our query included the following terms: spatial regressions, hotspots, multi-criteria, remote sensing, GPS, VGI; with the words "COVID-19" and "GIS" or "spatial" in Web of Sciences, Scopus, Mendeley, Collabovid, and Google Scholar. The selected papers in this review are the ones that were published between June 2020 and December 2020. Under our heuristic approach to the subject-matter, we have identified 221 articles that met our criteria.

Next, we were able to identify and group the studies into key topics as follows: (a) socioeconomic (demographic characteristics, gross domestic product, behavioral habits, inequality, and poverty indicators); (b) air, land, and hydrosphere pollution; (c) climate; (d) population mobility; (e) infrastructure and health services; and (f) COVID-19 data (confirmed cases, surveys, testing, crowdsourced data).

Regarding the objectives and utilities of these studies, we further categorized the studies into the following sub-topics: (a) spatiotemporal analysis of lockdowns; (b) spatial correlation and autocorrelation; (c) maps of risks and social vulnerability; (d) city planning and urban context; (e) regional and territorial analysis; (f) impacts of political decisions regarding preventative measures adopted in each country or study area; and (g) knowledge dissemination.

Within the 221 selected publications the following tools and techniques applied were identified: (a) spatial statistics, including spatial regressions (spatial lag model, spatial error model, combined autoregressive model, geographically weighted regression, multiscale geographically weighted regression, geographically weighted principal component analysis, Clifford correlation), hotspots and clustering (Getis–Ord *Gi*, kernel density, Moran's *I*, local Geary, geographic monitoring for early disease detection (GeoMEDD), self-organizing maps (SOMs) or Kohonen networks, scan statistics, *K*-medoid), geostatistics and interpolations (inverse distance weighting (IDW), Voronoi, kriging, cokriging, splines), other models (Markov, geodetector, birthday paradox, two-step floating catchment area, topological weighted centroid, self-organizing maps), and aspatial models in GIS (Poisson regression, Cox, Pearson, Spearman and Kendall, *K*-means, susceptible–infected–removed (SIR) models); (b) multicriteria analysis, including analytic hierarchy process, GIS multi-criteria decision analysis; (c) remote detection and unmanned aerial vehicles (UAVs); (d) data mining and networks; (e) web maps; and (f) volunteered geographic information (VGI) and public participatory GIS (PPGIS).

We have summarized the tools, thematic variables and objectives that we have identified in Figure 1.

3 | RESULTS

3.1 | Spatial statistics and COVID-19

Spatial statistics have mainly been used to analyze the socioeconomic and demographic risk factors of COVID-19 (Iyanda et al., 2020; Sannigrahi, Pilla, Basu, Basu, & Molter, 2020; Sun, Matthews, Yang, & Hu, 2020; Urban & Nakada, 2021). Air quality (Maiti et al., 2020; Zulkarnain & Ramadani, 2020), health infrastructure (Mollalo, Vahedi, & Rivera, 2020), and mobility (Nian et al., 2020) have also been examined and linked to COVID-19 risk and transmission. We have seen an influx of both spatial and spatiotemporal statistical methods applied to COVID-19, with many studies utilizing the results to produce risk and social vulnerability maps.

3.1.1 | Spatial regressions

In spatial modeling studies, it is common to start with ordinary least squares (OLS) regression to identify significant relationships between the dependent and independent variables. If the residuals of an OLS model are spatially autocorrelated, then it is appropriate to use spatial regression-based methods (Delmelle, Hagenlocher, Kienberger, & Cases, 2016). For example, a *spatial lag model* (SLM) can be used to examine how events at a location influence similar events in surrounding locations (i.e., spatial interaction); and a *spatial error model* (SEM) can be applied to account for autocorrelation of the residuals (Iyanda et al., 2020; Maiti et al., 2020; Mollalo, Vahedi, et al., 2020; Nian et al., 2020; Sannigrahi et al., 2020; Sun, Di, Sprigg, Tong, & Casal, 2020; Urban & Nakada, 2021); see Table 1. For COVID-19, *spatially combined autoregressive models* (SAC) have also been used as a combination

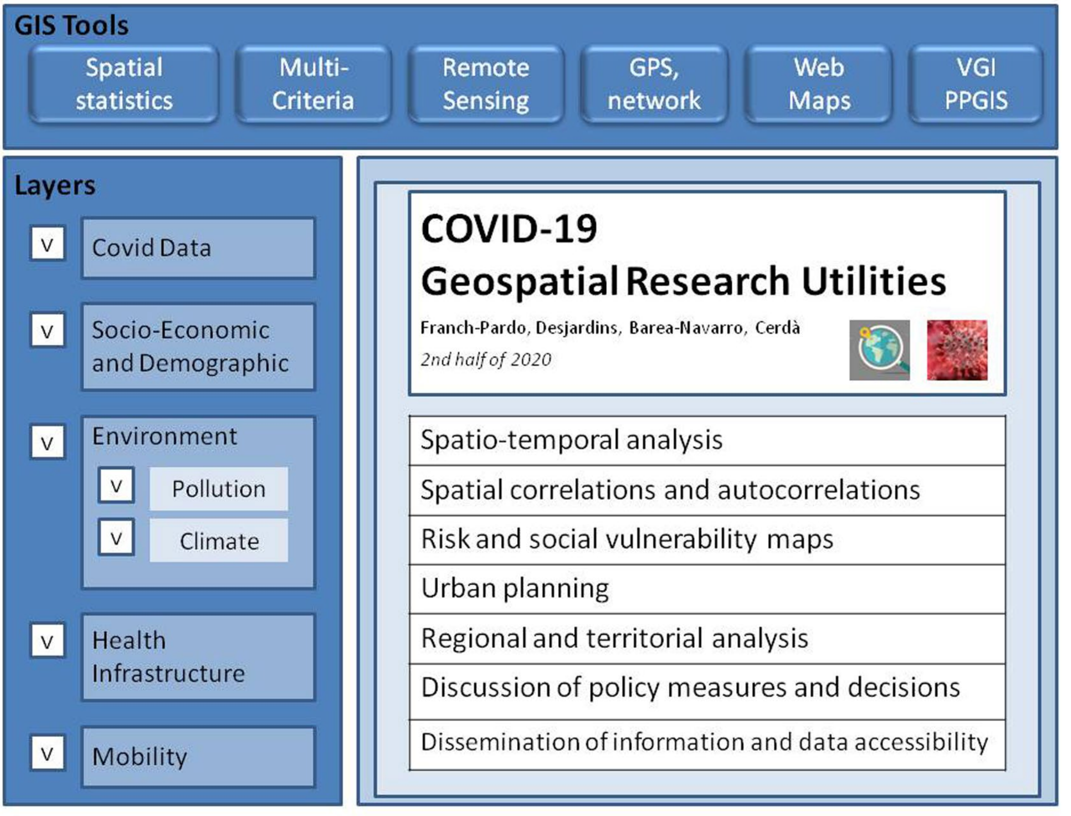

FIGURE 1 Graphical summary of the GIS tools, thematic variables used, and objectives categorized in this review

of the previous models to simultaneously consider spatial lag and spatial error parameters (Sun, Di, et al., 2020; Zulkarnain & Ramadani, 2020).

Another common method is *geographically weighted regression* (GWR), using the variables previously included in OLS regression (Alkhaldy, 2020; Fan, Zhan, Yang, Liu, & Zhan, 2020; Iyanda et al., 2020; Karaye & Horney, 2020; Shariati, Jahangiri-rad, Mahmud Muhammad, & Shariati, 2020; Urban & Nakada, 2021; Wu et al., 2020). GWR creates a local model and calculates the parameters for all points of the sample considering the spatial variation in the relationships (Brunsdon, Fotheringham, & Charlton, 1996; Maiti et al., 2020). It can consider non-stationary variables (such as climate, demographic factors, and environmental factors) and models the local relationships between those predictors and the patterns under study. It facilitates the analysis of spatial variation in a phenomenon in a given place (Murgante et al., 2020), following Tobler's first law of geography—that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Regarding COVID-19, GWR has been used to examine the relationships between the disease and air quality and a variety of socio-economic variables. For example, Fan et al. (2020) applied GWR and other models to assess the evolution of air pollution during 2020 in urban contexts in China. Murgante et al. (2020) examined the geographic parallels between affected areas in the Po Valley, Italy, and Wuhan, China, where they found that pollution and land use play an important role in the distribution of COVID-19 in both regions. Mansour, Al Kindi, Al-Said, Al-Said, and Atkinson (2020) used GWR to identify relationships between sociodemographic variables (population density, age groups, diabetics) and COVID-19 in Oman.

TABLE 1 Spatial statistics

					Variables used					Specific topics and analysis					
Tools		Study	Region or country of study	Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
Spatial regressions	SLMs, SEMs	Iyanda et al. (2020)	World	×	×				Confirmed cases	×	×			×	
		Sannigrahi et al. (2020)	Europe	×	×				Confirmed cases						
		Maiti et al. (2020)	USA	×	×	×			Confirmed cases	×					
		Mollalo, Vahedi, et al. (2020)	USA	×	×	×	×		Confirmed cases		×				
		Sun, Di, et al. (2020)	USA						Confirmed cases	×	×	×			
		Urban and Nakada (2021)	Brazil	×	×				Confirmed cases	×		×	São Paulo		
		Nian et al. (2020)	China	×	×	×		×		×			Chongqing	×	Economic repercussions
	SAC	Sun, Di, et al. (2020)	USA						Confirmed cases	×	×				
		Zulkarnain and Ramadani (2020)	Indonesia			×			Confirmed cases	×	×			×	
	GWR	Wu et al. (2020)	China	×	×		×	×	Confirmed cases		×		×		
		Iyanda et al. (2020)	World	×	×				Confirmed cases	×	×			×	
		Karaye and Horney (2020)	USA	×	×	×	×		Confirmed cases		×	×			
		Maiti et al. (2020)	USA	×	×	×			Confirmed cases	×					
		Murgante et al. (2020)	China, Italy			×	×		Confirmed cases	×	×		Wuhan, Milan		
		Mansour et al. (2020)	Oman	×	×				Confirmed cases		×				
		Fan et al. (2020)	China	×	×	×	×		Confirmed cases	×	×		×		
		Shariati, Jahangiri-rad, et al. (2020)	Iran	×	×	×	×		Confirmed cases	×		×			
		Liu, He, and Zhou (2020)	China	×	×			×	Confirmed cases	×					
		Liu, Wang, et al. (2020)	China	×	×			×	Confirmed cases	×					Predictive modeling
		Urban and Nakada (2021)	Brazil	×	×				Confirmed cases	×		×	São Paulo		
		Cheng et al. (2020)	China					×	Confirmed cases	Lockdown				×	
		Alkhaldy (2020)	Saudi Arabia	×	×			×	Confirmed cases			×			

(Continues)

TABLE 1 (Continued)

Tools		Study	Region or country of study	Variables used: Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
		Liang, Wang, Sun, Liang, and Li (2020)	China	×	×			×	Confirmed cases	×			×		
		He et al. (2020)	China	×	×	×			Confirmed cases	×					
		Li, Zhou, et al. (2020)	China	×	×				Confirmed cases	×		×	Wuhan		
		Bag, Ghosh, Biswas, and Chatterjee (2020)	India	×	×				Confirmed cases	×		×			Territorial planning
	MGWR	Iyanda et al. (2020)	World	×	×				Confirmed cases	×	×			×	
		Sannigrahi et al. (2020)	Europe	×	×				Confirmed cases		×				
		Maiti et al. (2020)	USA	×	×	×			Confirmed cases	×					
		Mollalo, Vahedi, et al. (2020)	USA	×	×	×	×		Confirmed cases		×				
		Fan et al. (2020)	China	×	×	×	×		Confirmed cases	×	×		×		
		Liu, He, et al. (2020)	China	×	×			×	Confirmed cases	×					
		Urban and Nakada (2021)	Brazil	×	×				Confirmed cases	×		×	São Paulo		
	GWPCA	Das et al. (2021)	India	×	×			×	Confirmed cases				Kolkata	×	
	Clifford	Nomura et al. (2020)	Japan	×	×				Confirmed cases	×		×	Fukuoka	×	Urban planning
Hotspots and clustering	Getis–Ord *Gi*	Sugg et al. (2020)	USA	×	×				Confirmed cases						
		Barboza et al. (2021)	USA	×	×				Confirmed cases	×		×	Los Angeles		
		Baum and Henry (2020)	USA	×	×				Confirmed cases		×				
		Fang et al. (2020)	China							×		×	Xiamen		Urban planning
		Mollalo, Vahedi, Bhattarai, et al. (2020)	USA	×	×	×	×		Confirmed cases	×	×				
		Shariati, Jahangiri-rad, et al. (2020)	Iran	×	×	×	×		Confirmed cases	×		×			
		Al-Kindi et al. (2020)	Oman						Polls and confirmed cases	×					
		Mollalo, Rivera, and Vahedi (2020)	USA	×	×				Confirmed cases	×	×				

(Continues)

TABLE 1 (Continued)

			Variables used						Specific topics and analysis					
Tools	Study	Region or country of study	Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Maroko et al. (2020)	USA	×	×				Confirmed cases	×	×		New York, Chicago		
	Islam et al. (2021)	South Asia	×	×				Confirmed cases	×	×			×	
	Shariati, Mesgari, et al. (2020)	World	×	×				Confirmed cases	×	×				
	Rahman, Islam, et al. (2020)	Bangladesh	×	×				Confirmed cases	×	×				Regional geography
	Bag et al. (2020)	India	×	×				Confirmed cases	×		×			Territorial planning
	Geng et al. (2020)	USA						Confirmed cases	×	×			×	
	Cos, Castillo, and Cantarer. (2020)	Spain	×	×				Confirmed cases	×		×		×	Territorial planning
	Rex et al. (2020)	Brazil	×	×				Confirmed cases			×	×	×	
	Nian et al. (2020)	China	×	×	×		×		×			Chongqing	×	Economic repercussions
Moran's *I*	Harris (2020)	UK	×	×				Confirmed cases	×	×		London		
	Wu et al. (2020)	China	×	×		×	×	Confirmed cases		×		×		
	Iyanda et al. (2020)	World	×	×				Confirmed cases	×	×			×	
	Murgante et al. (2020)	China, Italy			×	×		Confirmed cases	×			Wuhan, Milan		
	Baum and Henry (2020)	USA	×	×				Confirmed cases		×				
	Mollalo, Vahedi, Bhattarai, et al. (2020)	USA	×	×	×	×		Confirmed cases	×	×				
	Huang and Brown (2021)	Germany	×	×	×	×		Confirmed cases			×		×	
	Kang, Choi, et al. (2020)	China	×	×				Confirmed cases	×					
	Santana Juárez et al. (2020)	Mexico						Confirmed cases	×					
	Sun, Di, et al. (2020)	USA						Confirmed cases	×	×	×			
	Xie et al. (2020)	China					×	Confirmed cases	×	×				
	Yao, Pan, et al. (2020)	China	×	×	×			Confirmed cases	×	×		×		

(Continues)

TABLE 1 (Continued)

Tools	Study	Region or country of study	Variables used: Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Shariati, Jahangiri-rad, et al. (2020)	Iran	x	×	×	×		Confirmed cases	×		×			
	Liu, He, et al. (2020)	China	x	×			×	Confirmed cases	×					
	Fan et al. (2020)	China	x	×	×	×		Confirmed cases	×	×		×		
	Kim and Castro (2020)	South Korea	x	×				Confirmed cases	×	×			×	
	Gomes et al. (2020)	Brazil						Confirmed cases	×		×			
	Andrades-Grassi et al. (2020)	Europe and Maghreb	x	×			×	Confirmed cases			×			
	Liu, Fang, et al. (2020)	China	x	×			×	Internet and confirmed cases	×		×	×		
	Al-Kindi et al. (2020)	Oman						Polls and confirmed cases	×					
	Maroko et al. (2020)	USA	x	×				Confirmed cases	×	×		New York, Chicago		
	Alcântara et al. (2020)	Brazil	x	×				Confirmed cases		×				
	Shariati, Mesgari, et al. (2020)	World	x	×				Confirmed cases	×	×				
	Bag et al. (2020)	India	x	×				Confirmed cases	×		×			Territorial planning
	Nian et al. (2020)	China	x	×	×		×		×			Chongqing	×	Economic repercussions
Geary's C	Alcântara et al. (2020)	Brazil	x	×				Confirmed cases		×				
GeoMEDD	Curtis et al. (2020)	USA	x	×			×	Confirmed cases				×	×	Regional geography
SOMs	Melin et al. (2020)	World						Confirmed cases	×					Regional geography
Scan statistics	Andersen et al. (2020)	USA	x	×				Confirmed cases		×	×			

(Continues)

TABLE 1 (Continued)

Tools		Study	Region or country of study	Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
					Variables used					Specific topics and analysis					
		Wang, Liu, Struthers, and Lian (2020)	USA	x	×			×	Confirmed cases	×		×			
	K-medoid	Pászto and Vondráková (2020)	Europe	x	×			×	Confirmed cases	×					
	Not specified	Pollán et al. (2020)	Spain	x	×				Serological surveys						
		Gianquintieri et al. (2020)	Italy	x	×				Confirmed cases	×					Territorial planning
		Sahraoui et al. (2020)	Algeria					×	Thermal camera sensors				Annaba		
		Oster et al. (2020)	USA	x	×				Confirmed cases	×		×			
		Kanga et al. (2020)	India	x	×							×	Jaipur		Urban planning
		Zhang and Schwartz (2020)	USA	x	x				Confirmed cases		x				
		Ghosh and Mollah (2020)	Bangladesh	x	×			×	Confirmed cases	×		×			
		Adler, Florida, and Hartt (2020)	USA	x	×				Confirmed cases	×		×		×	
		Ash'aari et al. (2020)	Malaysia			×	×		Confirmed cases	×	×				
		Hu, Yue, et al. (2020)	USA	x	×				Testing sites and confirmed cases		×				
Interpolation and geostatistics	IDW	Prunet et al. (2020)	France, Italy, Spain, Greece			×				Lockdown			Paris, Milan, Madrid, Athens	×	
		Saha et al. (2020)	India					×		Lockdown				×	
		Layati, Ouigmane, de Carvalho Alves, Murugesan, and El Ghachi (2020)	Morocco	x	×				Confirmed cases		×				
		Bag et al. (2020)	India	x	×				Confirmed cases	×		×			Territorial planning

(Continues)

TABLE 1 (Continued)

				Variables used						Specific topics and analysis					
Tools		Study	Region or country of study	Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Voronoi	Bherwani et al. (2020)	India						Confirmed cases					x	
	Spline	Sui et al. (2020)	China			×		×	Polls	×	×		Qingdao		Urban planning, environmental repercussions
		Gupta, Banerjee, and Das (2020)	India	x	×		×		Confirmed cases		×				Regional geography
		Dickson, Espa, Giuliani, Santi, and Savadori (2020)	Italy						Confirmed cases	Lockdown				×	
	Kriging	Yao, Pan, et al. (2020)	China	x	×	×			Confirmed cases	×	×		×		
		Ran et al. (2020)	China			×	×		Confirmed cases	×			×		
		Yao, Zuo, et al. (2020)	China	x	×		×		Confirmed cases	×	×				Land use, environmental repercussions
		Wei et al. (2020)	China					×	Confirmed cases		×				
		Sarfo and Karuppannan (2020)	Ghana						Confirmed cases	×				×	
		Huang and Brown (2021)	Germany	x	×	×	×		Confirmed cases		×	×		×	
		Saha and Chouhan (2021)	India					×		Lockdown	×			×	
		Jain and Sharma (2020)	India	x	×	×	×	×		Lock-down	×		Delhi, Mumbai, Chennai, Kolkata, Bangalore	×	
		Ash'aari et al. (2020)	Malaysia			×	×		Confirmed cases	×	×				
		Kerimray et al. (2020)	Kazakhstan			×	×	×		Lockdown	×		Almaty	×	
Other models	Markov	Dehghan Shabani and Shahnazi (2020)	Asia						Confirmed cases	×				×	Predictive modeling
		Krisztin et al. (2020)	World					×	Confirmed cases	×					

(Continues)

TABLE 1 (Continued)

				Variables used						Specific topics and analysis					
Tools		Study	Region or country of study	Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Geodetector	Wu et al. (2020)	China		×		×	×	Remote sensing and confirmed cases		×		×		
		Xie et al. (2020)	China	x				×	Confirmed cases	×	×				
		Zhang, Li, Yang, Zheng, and Chen (2020)	China		×			×	Confirmed cases			×	Wuhan	×	Urban planning
		Hu, Qiu, et al. (2020)	China	x				×	Confirmed cases	×					
	Spatial ABM	Gharakhanlou & Hooshangi, 2020	Iran		×			×	Confirmed cases	×			Urmia	×	Urban planning
		Prudhomme et al. (2020)	France	x	×			×	Confirmed cases				Dijon	×	Urban planning
	2SFCA	Tao et al. (2020)	USA	x	×			×	Testing sites and confirmed cases						Territorial planning
	Birthday paradox	Sun, Di, et al. (2020)	USA	x					Confirmed cases	×	×				
	TWC	Buscema et al. (2020)	Italy						Confirmed cases	×					
	SUR	Paez, Lopez, Menezes, Cavalcanti, and Pitta (2020)	Spain		×		×		Confirmed cases	×	×				
	Spatiotemporal refined risk model	Michalak et al. (2020)	Poland	x					Confirmed cases	×					
Aspatial models	Poisson	Huang, Kwan, et al. (2020)	China		×				Confirmed cases		×	×	Hong Kong		Land use
		Yip et al. (2020)	China	x	×			×		×		×	Hong Kong	×	Urban planning
		Harris (2020)	UK	x	×				Confirmed cases	×	×		London		
		Andersen et al. (2020)	USA	x	×				Confirmed cases			×			

(Continues)

TABLE 1 (Continued)

Tools	Study	Region or country of study	Variables used: Demographic and socio-economic	Variables used: Contamination	Variables used: Weather	Variables used: Mobility	Variables used: Health services	Variables used: COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Specific topics and analysis: Correlations	Specific topics and analysis: Risk maps	Specific topics and analysis: Urban context	Specific topics and analysis: Political measures in research	Specific topics and analysis: Geographic specifications
	Desjardins, Hohl, and Delmelle (2020)	USA	x					Confirmed cases	×					Territorial planning
	Hohl et al. (2020)	USA						Confirmed cases	×		×			
	Das et al. (2021)	India		×			×	Confirmed cases		×		Kolkata	×	
	Sugg et al. (2020)	USA	x	×				Confirmed cases		×				
	Kim and Castro (2020)	South Korea	x	×				Confirmed cases	×	×			×	
	Gomes et al. (2020)	Brazil	x					Confirmed cases	×		×			
	Gayawan et al. (2020)	Africa		×				Confirmed cases	×		×			
	DiMaggio et al. (2020)	USA	x	×				Confirmed cases	×		×	New York		
	Ballesteros et al. (2021)	Ecuador	x					Confirmed cases	×		×			
	Lieberman-Cribbin, Tuminello, Flores, and Taioli (2020)	USA		×				Confirmed cases			×	New York		
	Samuels-Kalow et al. (2020)	USA	x					Confirmed cases	×			Boston		
	Andrades-Grassi et al. (2020)	Europe and Maghreb		×			×	Confirmed cases			×			
		USA	x	×				Confirmed cases				×		Urban planning
	Krisztin et al. (2020)	World	x				×	Confirmed cases	×					
	Saez et al. (2020)	Spain		×	×			Confirmed cases	×		×			
	Dickson et al. (2020)	Italy	x					Confirmed cases	Lockdown				×	
Cox regression	Fortaleza et al. (2020)	Brazil		×				Confirmed cases			×	×		Regional geography
	Hutter et al. (2020)	Austria	x	×	×			Confirmed cases				Vienna		
Pearson	Wu et al. (2020)	China	x	×		×	×	Confirmed cases		×		×		
	Mollalo, Vahedi, Bhattarai, et al. (2020)	USA	x	×	×	×		Confirmed cases	×	×				
	Chatterjee et al. (2020)	India	x	×			×	Confirmed cases	×		×		×	

(Continues)

TABLE 1 (Continued)

Tools	Study	Region or country of study	Variables used: Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Bherwani et al. (2020)	India	x					Confirmed cases					×	
	Tao et al. (2020)	USA		×			×	Testing sites and confirmed cases						Territorial planning
	Marquès et al. (2020)	Spain	x		×			Confirmed cases						
	Tello-Leal and Macías-Hernández (2020)	Mexico			×			Confirmed cases	Lockdown			Victoria		
	Mollalo, Rivera, et al. (2020)	USA		×				Confirmed cases	×	×				
	Meraj et al. (2021)	India	x			×		Confirmed cases	×	×				
	Li, Wang, et al. (2020)	China		×				Confirmed cases	×	×				
	Vergara-Perucich et al. (2020)	Chile	x	×				Confirmed cases	×	×		Santiago de Chile		Urban planning
	Oxoli, Cedeno Jimenez, and brovelli (2020)	Italy	x		×			Remote sensing	Lockdown					Regional geography, environmental repercussions
	Hu, Qiu, et al. (2020)	China					×	Confirmed cases	×					
Spearman and Kendall	Sun, Di, et al. (2020)	USA						Confirmed cases	×	×	×			
	Prunet et al. (2020)	France, Italy, Spain, Greece			×				Lockdown			Paris, Milan, Madrid, Athens	×	
	Pani et al. (2020)	Singapore				×		Confirmed cases	×	×		Singapore		
	Ran et al. (2020)	China			×	×		Confirmed cases	×	×		×		
	Urban and Nakada (2021)	Brazil		×				Confirmed cases	×	×	×	São Paulo		
	Nakada and Urban (2020)	Brazil	x	×		×		Confirmed cases	×	×		São Paulo	×	Urban planning
	Husnayain et al. (2020)	South Korea	x	×				Confirmed cases	×	×				
	Kuzmenko et al. (2020)	Ukraine	x	×		×		Confirmed cases	×	×				
K-means	Huang, Li, et al. (2020)	USA	x	×			×		×			Atlanta	×	

(Continues)

TABLE 1 (Continued)

Tools	Study	Region or country of study	Variables used: Demographic and socio-economic	Contamination	Weather	Mobility	Health services	COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Gan et al. (2020)	China	x				×	Confirmed cases	×		×	Shanghai		
	Lai et al. (2020)	USA		×			×	Confirmed cases	Lockdown	×		×		
	Abdallah et al. (2020)	Egypt	x				×	Confirmed cases						
SIR models	Thomas et al. (2020)	USA		×				Confirmed cases				×		
	O'Sullivan et al. (2020)	New Zealand	x	×				Confirmed cases	Lockdown				×	Regional geography
	Geng et al. (2020)	USA	x					Confirmed cases	×	×			×	

GWR has the limitation of assuming that all the processes that are modeled operate on the same spatial scale, which led to the development of *multiscale geographically weighted regression* (MGWR) where modeling can be applied at different spatial scales (Fotheringham, Yang, & Kang, 2017; Maiti et al., 2020). Iyanda et al. (2020) used MGWR to identify significant sociodemographic and economic factors of COVID-19 at the country level. Sannigrahi et al. (2020) estimated local spatial correlation coefficients between sociodemographic variables and COVID-19 data in Europe. Mollalo, Vahedi, et al. (2020), on the other hand, used MGWR for a local-level examination of the spatial non-stationarity between 35 environmental, socioeconomic, topographic, and demographic variables in the United States.

Geographically weighted principal component analysis (GWPCA) is an extension of the classic principal component analysis that adapts the approach for use with geographic data by considering spatial heterogeneity (Fernández, Cotos-Yáñez, Roca-Pardiñas, & Ordóñez, 2018). For COVID-19, Das et al. (2021) use GWPCA in developing their improved Index of Multiple Deprivations in districts of Kolkata, India, using housing conditions, household amenities, water, sanitation, and hygiene, asset possession, and gender disparity.

Nomura et al. (2020), in the prefecture of Fukuoka, Japan, used a modified test of spatial correlation coefficients (Clifford, Richardson, & Hémon, 1989) to relate the number of PCR-confirmed COVID-19 cases to a social network application that provides real-time monitoring of self-reported COVID-19 symptoms. The highly significant correlation they report indicates the utility of crowdsourced data in spatial analysis, which can assist in policy evaluations such as emergency declarations.

3.1.2 | Hotspots and clustering

Another common method utilized to study COVID-19 is *hotspot analysis* (Table 1), which can facilitate targeted interventions by local, state, and federal agencies. Two of the most common tools to measure local clustering is the Getis–Ord *Gi* statistic and kernel density. The *Gi* statistic uses a global index to measure the level of spatial autocorrelation, that is, the degree to which objects or activities in a geographic unit are similar to other objects or activities in nearby geographic units (Goodchild, 1987). It has been used in numerous studies to understand the distribution of COVID-19 cases, their spatial evolution over time, and for vulnerability and risk maps (e.g., Al-Kindi et al., 2020; Barboza, Schiamberg, & Pachl, 2021; Maroko, Nash, & Pavilonis, 2020; Mollalo, Vahedi, Bhattarai, et al., 2020; Rahman, Islam, & Islam, 2020).

Kernel density estimation (KDE) is used to estimate data densities that do not have parametric statistical behaviors, that is, do not follow normal, binomial, or exponential distributions (Okabe, Satoh, & Sugihara, 2009). Rex, Borges, and Käfer (2020) applied KDE to identify areas with a high density of COVID-19 cases; and Nian et al. (2020) examined public transport mobility data.

Following the review of spatial autocorrelation methods, the global univariate *Moran's I* method is the most widely used, although it has mainly been utilized with socioeconomic and COVID-19 data. It can evaluate whether the data tend to be clustered, dispersed, or spatially random. It has been used to identify clustering of COVID-19 (Alcântara et al., 2020; Baum & Henry, 2020; Kang, Choi, Kim, & Choi, 2020; Liu, Fang, & Gao, 2020; Wu et al., 2020) and facilitate the production of vulnerability and risk maps (e.g., Andrades-Grassi et al., 2020; Gomes et al., 2020; Shariati, Mesgari, Kasraee, & Jahangiri-Rad, 2020).

As a global indicator, Moran's *I* neglects the instability of local spatial processes, which led to the development of the local version of Moran's *I* (Anselin, 1995) which identifies both the spatial clustering of entities with similar values and the occurrence of divergent values. This latter version is also known as a *local indicator of spatial association* (LISA). Xie et al. (2020) and Wu et al. (2020) in China, Murgante et al. (2020) and Sun, Di, et al. (2020) in the United States, and Santana Juárez, Castañeda, Carillo, Carillo, and Alcántara (2020) in Mexico produced LISA cluster maps to analyze the characteristics of COVID-19 at various spatial levels of aggregation.

Other prominent clustering techniques are:

- *Self-organizing maps*, also known as Kohonen networks, a particular type of unsupervised neural network that performs spatial groupings of data based on similar behaviors. Melin et al. (2020) used a self-organizing map to examine COVID-19 cases in various countries.
- Spatial *scan statistics* (Kulldorf, 2018) to identify significant clusters of cumulative COVID-19 cases (Andersen, Harden, Sugg, Runkle, & Lundquist, 2020).
- *GeoMEDD* (Curtis et al., 2020) is a new real-time cluster detection methodology that provides indicators on the spatial evolution of the disease, based on access to various public sources that account for the location and timing of cases.

3.1.3 | Interpolation and geostatistics

Here we focus on the *interpolation methods* used in works that address the spatial and spatiotemporal patterns of the pandemic, associated with atmospheric themes (pollution and climate), but also socioeconomic ones (Table 1). Many works pay special attention to the severe lockdowns that have been imposed in different countries, mainly in Europe and Asia.

- *Inverse distance weighting* interpolation: Saha, Barman, and Chouhan (2020) analyzed the impact of the COVID-19 lockdown on community mobility in different Indian states and used IDW to show movement trends before and after the lockdown.
- *Voronoi*: Bherwani et al. (2020) used Bayesian probabilistic modeling to understand the relationship between COVID-19 cases and population density in a given region together with GIS-based Voronoi diagrams to identify high-risk areas. Thiessen polygons delineate the risk zone boundaries.
- *Geostatistics* estimate values of phenomena in areas where the values are uncertain or missing based on the covariance (how two random variables change) or variogram (spatial dependence among stochastic (random) processes); see Moral García (2004). *Spline* interpolations are another technique using discrete data points to model a continuous variable. Sui et al. (2020) used a cubic spline technique to estimate the second-by-second speed of buses and taxis through vehicle GPS data devices; they discuss the potential change in emissions in a post-COVID period.
- *Kriging* is probably the most commonly used geostatistical method and has been used in the COVID-19 literature to predict climatic variables (Sarfo & Karuppannan, 2020; Wei et al., 2020; Yao, Zuo, et al., 2020; Yao, Pan, et al., 2020) and common atmospheric contaminants (Huang & Brown, 2021; Ran et al., 2020). In the latter case, research has used kriging to identify associations between air pollution and COVID-19. A related technique is *cokriging*. Kerimray et al. (2020) use cokriging to map distributions of PM 2.5 and benzene in Almaty, Kazakhstan, in 2018–2019 and 2020, respectively. In particular, they examined the effect of government-mandated lockdowns on concentrations of the pollutants.

3.1.4 | Other spatial models

We mention other models used (Table 1).

- *Spatial Markov* (Dehghan Shabani & Shahnazi, 2020; Gayawan et al., 2020; Krisztin, Piribauer, & Wögerer, 2020) is a method where the probability of an event occurring depends only on the immediately preceding event, characterizing the spatial evolution of COVID-19.

- *Geodetector* (Hu, Qiu, et al., 2020; Wu et al., 2020; Xie et al., 2020) is a method to detect stratified spatial heterogeneity and determine related factors, in this case with COVID-19.
- Spatial *agent-based models* (ABM), which are popular in the study of epidemics, simulate the spatial behavior of the agents (population in this case), identifying the areas with the greatest concurrence, the population mobility, and the interactions between them. This can re-create and predict the appearance of COVID-19 cases based on expected social behavior. It has been applied in urban environments (Gharakhanlou & Hooshangi, 2020; Prudhomme, Cruz, & Cherifi, 2020)
- The *two-step floating catchment area* (2SFCA) method was used by Tao, Downs, Beckie, Chen, and McNelley (2020) to calculate the accessibility of COVID-19 testing sites in Florida.
- The *birthday paradox* is a probability model which was used to estimate the risks of exposure of populations to contagion (Sun, Di, et al., 2020).
- *Topological weighted centroid* (TWC; Buscema, Della Torre, Breda, Massini, & Grossi, 2020) is a new algorithm used in Italy to analyze the evolution of the outbreak and to predict future epidemic processes.
- The spatial *seemingly unrelated regression* (SUR) equations model can be used when the structure of the data consists of cross-sections for different time periods. Saez, Tobias, and Barceló (2020) analyzes the possible seasonality of COVID-19.
- The spatiotemporal *refined risk model* was used by Michalak et al. (2020) for the unbiased identification of time periods with high risk of COVID-19 in Poland.

3.1.5 | Aspatial models in GIS

There are studies that use aspatial models and methods in conjunction with GIS, which is also important to mention due to its geographical contribution to the study of the pandemic (Table 1).

- *Poisson regression* has been applied for COVID-19 in socioeconomic studies with health services infrastructure, especially in urban contexts (Ballesteros, Salazar, Sánchez, & Bolaños, 2021; DiMaggio, Klein, Berry, & Frangos, 2020; Saez et al., 2020; Yip, Huang, & Liang, 2020).
- *Pearson correlation* has been used with all kinds of variables, but especially with socioeconomic data, for spatiotemporal analysis, risk maps, health accessibility, and environmental repercussions due to the pandemic (Chatterjee et al., 2020; Li, Wang, Huang, & Lu, 2020; Marquès, Rovira, Nadal, & Domingo, 2020; Meraj et al., 2021; Tello-Leal & Macías-Hernández, 2020; Vergara-Perucich, Correa-Parra, & Aguirre-Nuñez, 2020).
- *Spearman and Kendall tests* have been used with confirmed cases of COVID-19 and socioeconomic variables, as well as with climate and air quality, to analyze the spatiotemporal evolution of the pandemic, mainly in urban contexts (Kuzmenko, Vasylieva, Vojtovič, Chygryn, & Snieška, 2020; Nakada & Urban, 2020; Pani, Lin, & RavindraBabu, 2020).
- *Cox regression* has been used to produce maps of vulnerability and risk in urban contexts (Fortaleza, Guimarães, de Almeida, Pronunciate, & Ferreira, 2020; Hutter et al., 2020).
- *K-means* is an unsupervised clustering algorithm that partitions the data based on the closest mean. In this review we identify those works that used it to perform clustering as part of the process of a spatial analysis. For example, Lai, Charpignon, Ebner, and Celi (2020) used it to group US counties based on sociodemographic characteristics and COVID-19 data; and Abdallah, Khafagy, and Omara (2020) for GPS location data.
- *SIR models* can add explicit geographical variables to study epidemic dynamics (Geng et al., 2020; O'Sullivan, Gahegan, Exter, & Adams, 2020; Thomas et al., 2020).

3.2 | Multicriteria analysis

The *analytic hierarchy process* (AHP) is a multicriteria decision-making model (Saaty, 1988). It is an additive and compensatory technique of pair-based comparison, based on three principles: decomposition, comparative evaluation, and establishment of priorities. It is a process for identifying, understanding, and evaluating the interactions of a system in a holistic way by providing a scale to measure intangible factors and a method to establish priorities (Requia, Kondo, Adams, Gold, & Struchiner, 2020). For COVID-19, it has been widely used for issues related to the environment and health geography through the development of maps of social vulnerability and risks, and health accessibility (Table 2). Requia et al. (2020) developed a hierarchical network for issues of land use, socioeconomics, population, health conditions, and the health-care system in Brazil. Mishra, Gayen, and Haque (2020) used AHP to generate a COVID-19 Vulnerability Index for urban environments in India, and Fang, Huang, Zhang, and Nitivattananom (2020) performed a similar analysis for the island of Xiamen, China.

With GIS tools, multi-criteria decision analysis (MCDA) has also been used (Table 2). It is a methodology to evaluate alternatives on specific topics, often conflicting, and combine them in a general evaluation (Albahri et al., 2020). Using this procedure, Sánchez-Sánchez, Chuc, Canché, & Uscanga (2020) created a population vulnerability model where they evaluate and map the susceptibility to the risk of contagion of COVID-19 in Chetumal, Mexico. Other similar examples are found in Kampala, Uganda (Bamweyana et al., 2020), and in Nepal (Maharjan et al., 2020).

3.3 | Remote sensing and unmanned aerial vehicles

3.3.1 | The atmosphere

Relevant atmospheric analyses (Table 3) tend to fall into one of two categories: climatic conditions or pollution. The spatiotemporal dynamics of climatic conditions and their relationship to COVID-19 have been analyzed at many scales (Aman, Salman, & Yunus, 2020; El-Magd & Zanaty, 2020; Ghahremanloo, Lops, Choi, & Mousavinezhad, 2020; Mishra et al., 2020; Pei, Han, Ma, Su, & Gong, 2020; Rahman, Azad, et al., 2020; Wyche et al., 2020). Spatiotemporal analyses of pollution levels during the pandemic tend to focus on the consequence of reductions in mobility and economic production (Filonchyk, Hurynovich, Yan, Gusev, & Shpilevskaya, 2020; Sandifer et al., 2020; Wu et al., 2020). Special attention is paid to countries that imposed lockdowns to control the pandemic, as well as to issues specifically affecting urban areas (Das et al., 2021; Guida & Carpentieri, 2020; Kerimray et al., 2020; Prunet, Lezeaux, Camy-Payret, & Thevenon, 2020; Ran et al., 2020; Yao, Pan, et al., 2020). PM 2.5, PM 10, SO_2, NO_2, CO_2, O_3, O_x, and black carbon have been the most studied particles.

3.3.2 | The lithosphere

On the Earth's surface, remote sensing (RS) and UAVs have been used for studies of land use change, with significant examples such as the case of Yao, Zuo, et al. (2020) who analyze the potential distribution of soya crops and how COVID-19 has affected the soya market. Wang, Peng, et al. (2020) conducted a land use analysis of crops in China to evaluate whether the pandemic led to increased cultivation and land exploitation; their findings are relevant to the development of agricultural policy to improve food security. RS and UAVs also have applications for the real estate market as they are used for property inspection in a study that analyzes the consequences of COVID-19 on the real estate sector (Renigier-Biłozor, Zróbek, Walacik, & Janowski, 2020).

TABLE 2 Multicriteria

			Variables used						Specific topics and analysis					
Tools	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
AHP	Fang et al. (2020)	China							×		×	Xiamen		Urban planning
	Requia et al. (2020)	Brazil	×				×	Confirmed cases						Territorial planning
	Mishra et al. (2020)	India	×			×	×				×	Mumbai, Delhi, Chennai, Kolkata	×	
	Yao, Zuo, et al. (2020)	China	×		×			Confirmed cases	×	×				Land use, environmental repercussions
	Mahato, Bushi, and Nimasow (2020)	India	×				×	Confirmed cases	×		×		×	Territorial planning
	Rahman, Islam, et al. (2020)	Bangladesh	×					Confirmed cases	×					Territorial planning
	Sarkar (2020)	Bangladesh	×			×	×	Polls and confirmed cases			×		×	Territorial planning
	Ghosh, Das, et al. (2020)	India		×	×			Remote sensing	Lockdown			Mumbai, Delhi, Kolkata, Chennai		Normalized Difference Vegetation Index (NDVI)
	Habibi, Guellouh, Filali, and Berchiche (2020)	Algeria	×				×	Confirmed cases			×			Territorial planning
MCDA	Sánchez-Sánchez et al. (2020)	Mexico	×			×	×	Confirmed cases			×	Chetumal	×	Urban planning
	Maharjan et al. (2020)	Nepal	×					Confirmed cases			×			Territorial planning
	Bamweyana et al. (2020)	Uganda	×	×	×	×	×	Polls			×	Kampala		Urban planning

TABLE 2 (*Continued*)

Tools	Study	Region or country of study	Variables used						Specific topics and analysis					
			Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
Others	Karaye and Horney (2020)	USA	×	×	×			Confirmed cases			×			
	Wie et al. (2020)	China				×	×	Confirmed cases						
	Cuadros et al. (2020)	USA				×	×	Confirmed cases	×		×			Territorial planning
	Cos et al. (2020)	Spain	×				×	Confirmed cases	×		×		×	Territorial planning
	Sangiorgio and Parisi (2020)	Italy	×			×		Confirmed cases			×	×		Predictive modeling

TABLE 3 Remote sensing and unmanned aerial vehicles

			Variables used							Specific topics and analysis					
Earth spheres	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Remote sensing source	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
Atmosphere	Wu et al. (2020)	China	×		×	×		Confirmed cases	Gesopatial Data Cloud		×		×		
	Das et al. (2021)	India	×			×		Confirmed cases	*Landsat–8* OLI/ TIRS				Kolkata	×	
	Yao, Pan, et al. (2020)	China	×	×			×	Confirmed cases	China Meteorological Data Sharing Service System	×	×		×		
	Prunet et al. (2020)	France, Italy, Spain, Greece		×					*S5P* TROPOMI	Lockdown			Paris, Milan, Madrid, Athens	×	
	Yao, Zuo, et al. (2020)	China	×		×			Confirmed cases	Resource and Environmental Science Data Center of the Chinese Academy of Sciences	×	×				Land use, environmental repercussions
	Aman et al. (2020)	India		×					*Landsat-8* OLI/ TIRS	Lockdown			Ahmedabad		
	Pei et al. (2020)	China		×					*S5P* TROPOMI	Lockdown			Beijing, Wuhan, Guangzhou	×	
	Ghahremanloo et al. (2020)	East Asia		×					*S5P* TROPOMI	×				×	Environmental repercussions
	Wyche et al. (2020)	UK		×					*S5P* TROPOMI	×				×	Environmental repercussions
	Rahman, Azad, et al. (2020)	Bangladesh		×					*S5P* TROPOMI	Lockdown			x Dhaka	×	
	El-Magd and Zanaty (2020)	Egypt		×					MODIS	Lockdown				×	
	Stieb, Evans, To, Brook, and Burnett (2020)	Canada	×	×				Confirmed cases	MODIS, MISR, GEOS-Chem	×	×			×	NDVI
	Filonchyk et al. (2020)	China		×		×			MODIS, AIRS, AURA OMI	Lockdown				×	

TABLE 3 (*Continued*)

			Variables used							Specific topics and analysis					
Earth spheres	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Remote sensing source	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Stratoulias and Nuthammachot (2020)	Thailand		×					*S5P* TROPOMI	Lockdown					
	Ghosh, Das, et al. (2020)	India		×	×				*Landsat-8* OLI/TIRS	Lockdown			Mumbai, Delhi, Kolkata, Chennai		NDVI
	Roman-Gonzalez, Navarro-Raymundo, and Vargas-Cuentas (2020)	Peru		×					*S5P* TROPOMI	×				×	Environmental repercussions
	Metya, Dagupta, Halder, Chakraborty, and Tiwari (2020)	South-East Asia		×					AIRS, AURA OMI	Lockdown					
	Ogen (2020)	Europe		×					*S5P* TROPOMI	×					Environmental repercussions
	Vîrghileanu, Săvulescu, Mihai, Nistor, and Dobre (2020)	Europe		×		×		Confirmed cases	*S5P* TROPOMI	×	×				Regional geography
	Naeger and Murphy (2020)	USA		×	×				*S5P* TROPOMI	×				×	Regional geography, environmental repercussions
	Tan, Li, Gao, and Jiang (2020)	China		×					*S5P* TROPOMI	Lockdown				×	Regional geography, environmental repercussions
	Roman-González and Vargas-Cuentas (2020)	Peru		×					*S5P* TROPOMI	×					Environmental repercussions
	Sandifer et al. (2020)	USA	×		×			Polls	NOAA, IOOS			×			Territorial planning
	Lyalko, Yelistratove, Apstolov, and Romanciuc (2020)	Ukraine		×					*Envisat*, NOAA	Lockdown					Environmental repercussions

TABLE 3 (*Continued*)

Earth spheres	Study	Region or country of study	Variables used: Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Remote sensing source	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Evangeliou et al. (2020)	Europe		×	×				Global Atmosphere Watch	×					Environmental repercussions
	Oxoli et al. (2020)	Italy		×					*S5P* TROPOMI	Lockdown					Regional geography, environmental repercussions
	Pathakoti et al. (2020)	India		×	×				AURA OMI, *S5P* TROPOMI, MODIS	Lockdown				×	
	Ash'aari et al. (2020)	Malaysia		×		×			MODIS	Lockdown					Environmental repercussions
	Venter, Aunan, Chowdhury, and Lelieveld (2020)	World	×	×	×				*S5P* TROPOMI	Lockdown					Environmental repercussions
	Karaer, Balafkan, Gazea, Arghandeh, and Ozguven (2020)	USA		×		×			*S5P* TROPOMI	×	×				
Lithosphere	Das et al. (2021)	India	×			×		Confirmed cases	*Landsat 8* OLI/TIRS				Kolkata	×	
	Prunet et al. (2020)	France, Italy, Spain, Greece		×					*S5P* TROPOMI	Lockdown			Paris, Milan, Madrid, Athens	×	
	Yao, Zuo, et al. (2020)	China	×		×			Confirmed cases	Resource and Environmental Science Data Center of the Chinese Academy of Sciences	×	×				Land use, environmental repercussions
	Wang, Peng, et al. (2020)	China	×						Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences	×					Land use, environmental repercussions

TABLE 3 *(Continued)*

Earth spheres	Study	Region or country of study	Variables used: Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Remote sensing source	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Renigier-Biłozor et al. (2020)	World	×											×	Land use, economic repercussions
	Elvidge et al. (2020)	China	×			×			VIIRS, DNB, NOAA	×			×		Land use, economic and environmental repercussions
	Minetto et al. (2020)	World	×			×			*WorldView-2* satellite	×			Munich, Phoenix, Moscow, Wuhan, North Korea	×	Land use, economic repercussions
	Okyere et al. (2020)	Ghana	×			×			Unmanned aerial vehicle					×	Aquatic geoenvironments, urban planning, economic repercussions
	Mobaied (2020)	Syria	×									×		×	Land use
	Ghosh, Elvidge, et al. (2020)	India	×						VIIRS DNB NOAA	×					Land use, economic and environmental repercussions
	Taoyang et al. (2020)	China					×		*Gaofen-2*, *Jilin-1*, *Pléiades*	×			Wuhan		Urban planning
	Saxena, Rabha, Tahlani, and Ray (2020)	India			×				National Remote Sensing Center ISRO	×					Land use, NDVI, economic and environmental repercussions
	Gupta, Bhatt, Roy, and Chauhan (2020)	India			×				MODIS	Lockdown					Environmental repercussions, NDVI
	Kanga et al. (2020)	India	×				×		*WorldView-1*			×	Jaipur		Urban planning

TABLE 3 (*Continued*)

			Variables used							Specific topics and analysis					
Earth spheres	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Remote sensing source	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
Hydrosphere	Aman et al. (2020)	India		×					*Landsat-8* OLI/ TIRS	Lockdown			Ahmedabad		
	Okyere et al. (2020)	Ghana	×			×			UAV					×	Aquatic geoenvironments, urban planning, economic repercussions
	Garg et al. (2020)	India		×					*Sentinel-2A* and *Sentinel-2B*	Lockdown				×	Aquatic geoenvironments
	Yunus et al. (2020)	India		×					*S5P* TROPOMI, AURA OMI	Lockdown				×	Aquatic geoenvironments
	Rodríguez-Benito et al. (2020)	Chile		×					*Sentinel-2* and *Sentinel-3*	Lockdown				×	Aquatic geoenvironments
	Avtar et al. (2020)	China and India		×	×				*Landsat 8* OLI, *Sentinel-2*	Lockdown			Wuhan		Aquatic geoenvironments, environmental repercussions

Several studies have analyzed pollutant levels in urban environments (Das et al., 2021; Prunet et al., 2020). Lighting is considered an indicator of economic recovery or recession, as in the case of several Chinese cities, where lighting levels are compared during peak closure with the same variable a year earlier (Elvidge, Ghosh, Hsu, Zhizhin, & Bazilian, 2020).

Research on the dynamics of human movement during the pandemic demonstrates important applications of RS and UAVs. Minetto, Segundo, Rotich, and Sarkar (2020) employ a deep learning technique to automatically detect objects, such as cars and aircraft, from satellite imagery. They suggest that the ability to automatically identify these objects in a time series of images will allow for temporal analysis of societal indicators (Minetto et al., 2020). Similarly, Wu et al. (2020) use deep learning to identify vehicles within Wuhan, China, from RS imagery and thus evaluate the effect of a transportation ban on the city. In a very different type of analysis, Okyere et al. (2020) use UAVs to monitor fishing boats and assess adherence the effects of physical distancing mandates and risks of exposure in the fishing sector.

There are also studies in areas with armed conflict, as in the case of Syria (Mobaied, 2020). Using RS and spatial models, the authors designed the "Risk of Vulnerability to COVID-19 in War Zones Index" to identify areas that are vulnerable to the pandemic and thus help decision-makers to limit risk and avoid and/or manage widespread infection.

3.3.3 | The hydrosphere, with special attention to lockdowns

Addressing the concepts of rivers and pollution: changes in water quality as a result of a major lockdown have been evaluated in both the Ganges River (Garg, Aggarwal, & Chauhan, 2020) and the Sabarmati River (Aman et al., 2020) in India using *Landsat 8* and *Sentinel-2* imagery, respectively. Similar methods have been applied to measure lake pollution, such as by Yunus, Masago, and Hijioka (2020) who use *Landsat 8* to measure water turbidity in Vembanad Lake in India, finding an improvement in water quality as a result of lockdown.

In another hemisphere, *Sentinel-2* and *Sentinel-3* imagery was applied to detect a harmful algal bloom in salmonid aquaculture in Chile. The analysis technique, combined with rapid delivery of the high-resolution satellite imagery, allowed for near real-time monitoring and decision-making when in-situ sampling was restricted by a mandated lockdown (Rodríguez-Benito, Navarro, & Caballero, 2020).

RS and UAVs are also highly relevant to topics related to ocean economic activities. For example, a UAV was used in Ghana to monitor water-based activity during COVID-19, providing solid scientific evidence as a basis for decision-making in the artisanal fishing sector (Okyere et al., 2020).

3.4 | GPS and networks

Throughout this overview we have detailed numerous works employing GPS. Here we focus on data mining and analysis of communication and transportation networks (Table 4).

Studies using data mining to study human mobility tend to focus on areas where lockdowns have been established. We differentiate these studies by their inputs:

- Cellphone location (Arimura, Ha, Okumura, & Asada, 2020; Gao, Rao, et al., 2020; Kang, Gao, et al., 2020; Kapoor et al., 2020; Pepe et al., 2020; Roy & Kar, 2020; Yabe et al., 2020; Ye et al., 2020).
- Internet and social networks: Google (Husnayain, Shim, Fuad, & Su, 2020; Kapoor et al., 2020; Nguyen et al., 2020; Pászto & Vondráková, 2020), Baidu (Cheng et al., 2020; Liu, Fang, et al., 2020; Mu, Yeh, & Zhang, 2020; Shen, 2020; Shi et al., 2020; Tong, Ma, & Liu, 2020; Xu, Wang, Dong, Shen, & Xu, 2020), Facebook (Coven & Gupta, 2020; Heo, Lim, & Bell, 2020; Kuchler, Russel, & Stroebel, 2020), Twitter geotagged tweets

TABLE 4 GPS and networks

			Variables used								Specific topics and analysis					
Tools	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Info data mining	Source data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
Data mining	Yabe et al. (2020)	Japan				×		Confirmed cases	Mobile phone location	Agoop 20, NTT	×			Tokyo	×	
	Pepe et al. (2020)	Italy				×			Mobile phone location	Cuebiq Inc.	×				×	
	Arimura et al. (2020)	Japan	×			×		Confirmed cases	Mobile phone location	NTT DOCOMO	×			Sapporo		
	Lai et al. (2020)	USA	×			×		Confirmed cases	Mobile phone location	PlaceIQ	Lockdown	×		×		
	Gao, Rao, et al. (2020)	USA	×			×		Confirmed cases	Mobile phone location	SafeGraph	Lockdown				×	
	Kang, Gao, et al. (2020)	USA	×			×			Mobile phone location	SafeGraph	×				×	
	Roy and Kar (2020)	USA	×			×			Mobile phone location	SafeGraph	Lockdown			Los Angeles		
	Huang, Li, et al. (2020)	USA	×			×			Mobile phone location	SafeGraph	×			Atlanta	×	
	Ye et al. (2020)	China	×			×		Confirmed cases	Mobile phone location		×		×			
	Hu, Qiu, et al. (2020)	China				×		Confirmed cases	Mobile phone location							
	Gan et al. (2020)	China				×		Confirmed cases	Mobile phone location		×		×	Shanghai		
	Abdallah et al. (2020)	Egypt				×		Confirmed cases	Mobile phone location							
	Kapoor et al. (2020)	USA				×		Confirmed cases	Mobile phone location, internet	SafeGraph, Google	×				×	
	Sarfo and Karuppannan (2020)	Ghana						Confirmed cases	GPS	GH COVID-19 Tracker	×				×	
	He et al. (2020)	China	×	×				Confirmed cases	GPS	LBS Tencent	×					

TABLE 4 (*Continued*)

			Variables used								Specific topics and analysis					
Tools	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Info data mining	Source data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Guida and Carpentieri (2020)	Italy	×	×		×	×		GPS	OpenStreetMap, Agenzia Transporti Milanesi, GTFS				Milan	×	Urban planning
	Vannoni, McKee, Semezna, Bonell, and Stuckler (2020)	World				×			GPS	Citymapper	×			×	×	
	Nian et al. (2020)	China	×			×			GPS	Taxi	×			Chongqing	×	Environmental repercussions
	Depellegrin et al. (2020)	Italy	×			×			GPS	Boats (Automatic Identification System, AIS)	Lockdown			Venice	×	
	Pase et al. (2020)	USA	×			×			GPS	Citi Bike	×			New York	×	Urban planning
	Sui et al. (2020)	China		×		×		Polls	GPS	BUS public	×	×		Qingdao		Urban planning
	Sahraoui et al. (2020)	Algeria				×	×		GPS	Police and health departments vehicles				Annaba		
	Mu et al. (2020)	China	×		×	×		Confirmed cases	Internet	Baidu	×			×		
	Cheng et al. (2020)	China				×		Confirmed cases	Internet	Baidu	×				×	
	Shi et al. (2020)	China				×		Confirmed cases	Internet	Baidu			×			Territorial planning
	Xu et al. (2020)	China	×			×		Confirmed cases	Internet	Baidu	×			×		
	Shen (2020)	China				×		Confirmed cases	Internet	Baidu	×					
	Liu, Fang, et al. (2020)	China	×			×	×	Confirmed cases	Internet	Baidu	×		×	×		
	Tong et al. (2020)	China	×			×		Confirmed cases	Internet	Baidu	×				×	Regional geography
	Niu, yue, Zhou, and Zhang (2020)	China	×			×		Confirmed cases	Internet	Baidu				×		

TABLE 4 (*Continued*)

			Variables used								Specific topics and analysis					
Tools	Study	Region or country of study	Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Info data mining	Source data	Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Pászto and Vondráková (2020)	Europe	×			×		Confirmed cases	Internet	Google	×					Mapping techniques
	Husnayain et al. (2020)	South Korea	×					Confirmed cases	Internet	Google	×					
	Nguyen et al. (2020)	USA	×					Confirmed cases	Internet	Google Street View				×		Urban planning
	Coven and Gupta (2020)	USA	×			×			Social network	Facebook	×			New York	×	
	Heo et al. (2020)	USA	×			×			Social network	Facebook	×			×	×	Territorial planning
	Kuchler et al. (2020)	USA, Italy	×					Confirmed cases	Social network	Facebook						
	Yang et al. (2020)	World, USA	×	×		×		Confirmed cases	Social network	Geotagged Twitter	×				×	
	Li, Li, et al. (2020)	USA	×			×		Confirmed cases	Social network	Geotagged Twitter	×		×			
	Iranmanesh and Alpar Atun (2020)	Cyprus	×			×		Confirmed cases	Social network	Geotagged Twitter	×			Kyrenia		
	Zhu et al. (2020)	China	×					Confirmed cases	Social network	Qingbo Big Data Agency	×				×	
	Peng et al. (2020)	China	×					Confirmed cases	Social network	Weibo Data				Wuhan		Urban planning
Network	Valjarević et al. (2020)	World	×			×		Confirmed cases	Flights		×					Regional geography
	Sun, Wandelt, et al. (2020)	World				×			Flights		×					
	Saeed et al. (2021)	Pakistan	×			×	×	Confirmed cases	Geotagging COVID-19 cases		×			Punjab	×	Urban planning
	Taiwo (2020)	Nigeria	×			×	×	Testing sites and confirmed cases	Public services						×	Regional geography

TABLE 4 (*Continued*)

Tools	Study	Region or country of study	Variables used: Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Info data mining	Source data	Specific topics and analysis: Spatiotemporal analysis	Correlations	Risk maps	Urban context	Political measures in research	Geographic specifications
	Desmet and Wacziarg (2020)	USA	×		×	×	×	Confirmed cases	Public transport		×		×		×	Regional geography
	Saladié et al. (2020)	Spain	×			×			Road network		Lockdown				×	
	Wan (2020)	China				×		Confirmed cases	Road network		×			Beijing		
	Shah and Patel (2020)	India	×			×	×	Confirmed cases	Road network		×			Surat	×	Urban planning
	Bessa and da Luz (2020)	Brazil	×					Confirmed cases	Road network		×					Regional geography
	Snyder and Parks (2020)	USA	×	×	×		×		Road network, flights				×			Multi-criteria analysis
	Kanga et al. (2020)	India	×				×		Urban layout				×	Jaipur		Urban planning
	Silalahi et al. (2020)	Indonesia	×				×	Confirmed cases	Urban layout		×			Jakarta	×	
	Alasadi et al. (2020)	Iraq	×			×	×		Urban layout		×			Basra		Urban planning
	Deponte et al. (2020)	Italy	×			×			Urban layout					Milan		Urban planning
	Zecca et al. (2020)	Scotland	×						Urban layout					Aberdeen	×	Urban planning
	Liu, Lin, et al. (2020)	China				×	×		Urban layout					Wuhan		Urban planning

(Iranmanesh & Alpar Atun, 2021; Li, Li, et al., 2020; Saeed et al., 2021; Yang et al., 2020), Weibo (Peng, Wang, Liu, & Wu, 2020), Quingbo (Zhu, Zheng, Liu, Li, & Wang, 2020).
- Air and sea transport (Depellegrin, Bastianini, Fadini, & Menegon, 2020; Snyder & Parks, 2020; Sun, Wandelt, & Zhang, 2020; Valjarević et al., 2020).
- Monitoring of public transport: bus (Desmet & Wacziarg, 2020; Guida & Carpentieri, 2020; Sui et al., 2020), taxi (Nian et al., 2020), and urban bicycles (Pase, Chiariotti, Zanella, & Zorzi, 2020).
- Geotagged data for identified infections compiled with travel histories (He et al., 2020; Sarfo & Karuppannan, 2020).

On the use of layers on networks and transport flow, we emphasize the topics of road networks for accessibility to health services and the analysis of the change in the flow of vehicles due to lockdown (Bessa & da Luz, 2020; Desmet & Wacziarg, 2020; Saladié, Bustamante, & Gutiérrez, 2020; Shah & Patel, 2020; Snyder & Parks, 2020; Taiwo, 2020; Tao et al., 2020; Wan, 2020).

Studies on urban planning also occupy a very prominent space. As a result, the issue of health infrastructure and its accessibility is addressed, opening up a political debate about public spaces (Alasadi, Aziz, Dhiya, & Abdulmajed, 2020; Deponte, Fossa, & Gorrini, 2020; Kanga et al., 2020; Liu, Lin, et al., 2020; Silalahi, Hidayat, Dewi, Purwono, & Oktaviani, 2020; Zecca, Gaglione, Laing, & Gargiulo, 2020). We highlight the use of OSMnx tools to download spatial data from OpenStreetMap and model, project, visualize, and analyze street networks (Boeing, 2020).

3.5 | Web maps

Thanks to the availability of constantly updated open data and the availability of web maps, plugins, and code sharing, there are many geospatial platforms online for monitoring COVID-19 around the world (Ghilardi et al., 2020), which have emerged from organizations, academic institutions, or media platforms.

WebGIS platforms for the dissemination of information to the public and data accessibility have already been addressed in other previous works (Boulos & Geraghty, 2020; Franch-Pardo et al., 2020; Koller et al., 2020; Zúñiga et al., 2020). Some papers explain the technical operations of the web platform (Ghilardi et al., 2020; Graves & He, 2020; Hohl, Delmelle, Desjardins, & Lan, 2020; Mooney et al., 2020; Peddireddy et al., 2020; Sarfo & Karuppannan, 2020). Here we present a specific example in Mexico and briefly explain the operation of the university-based platform maintained by the National Autonomous University of Mexico (https://covid19.ciga.unam.mx/). The platform is supported by a package written in R, which runs a daily process to download the current COVID-19 data published by the federal government. The system first cross-checks the data publication date and downloads the database for the current day from the page maintained by the Health Agency. The data are combined with spatial data for the geographic regions (states and municipalities) and with 2020 population counts for the given regions. Next, the following statistics are calculated at the national, state, and municipal level: total recovered cases, active cases, deaths, and accumulated cases. Combining these totals with the population counts, the process computes rates of incidence, mortality, and fatality. The absolute change between consecutive weeks is calculated for weekly values for positive cases, hospitalizations, and deaths, as well as the weekly change in incidence and mortality rates, and the percent positivity rate (Ghilardi et al., 2020). These geographic data are mapped and published through an ArcGIS Online web dashboard using the template of the widely known dashboard created by Johns Hopkins University (Dong, Du, & Gardner, 2020).

In recent months, other notable graphics have been produced using cartograms to represent COVID-19 data worldwide (Yalcin, 2020), for China (Gao, Zhang, Wu, & Wang, 2020; Shi & Liu, 2020), Italy (Casti, 2020) and the United States (Zhang, 2020).

3.6 | Volunteered geographic information and public participation GIS

Green areas in cities, the layout of their streets, environmental quality, and public spaces play an important role in times of the pandemic (Honey-Roses et al., 2020; Samuelsson, Barthel, Colding, Macassa, & Giusti, 2020). PPGIS and VGI are important tools, in addition to existing information sources, for gathering data from the population to fight COVID-19 (Table 5). Gorayeb et al. (2020) describe information gathering through citizen surveys in Fortaleza, Brazil. The information provided by the population through the surveys exhibits similarities with data provided by official maps, suggesting that these are promising tools for rapid data collection. In Israel, an online questionnaire was carried out to identify possible symptoms and to follow up with infected persons over time (Rossman et al., 2020). In the interpretation of the data, differences in the proportion of reported symptoms in participants from different cities and different neighborhoods that are geographically close to each other are revealed, which could suggest the ability to detect changes at a high geographical resolution.

The implementation of PPGIS in Greece (Antoniou, Vassilakis, & Hatzaki, 2020) and India (Debnath & Bardhan, 2020) during the spring of 2020 was motivated by the need to rapidly acquire data based on location. These studies find that crowdsourcing applications are important tools for real-time mapping and monitoring to allow health authorities to make decisions and design effective management approaches (Antoniou et al., 2020; Brito et al., 2020; Desjardins, 2020).

4 | DISCUSSION

In the review of the first half of 2020 on GIS and spatial analysis prepared by Franch-Pardo et al. (2020), the authors alluded to the fact that Tobler's (1970) law was much less evident in the geographic analyses of COVID-19 due to the fact that numerous works conducted studies on global and national scales. This was largely because spatial analysis requires adequate spatial and spatiotemporal data sets, which was rare in the early months of 2020.

At first, the disease evolution patterns worldwide were more like Lévy's flight (Gross et al., 2020), in other words, randomly distributed, where human movement seemed to be the only driving factor for the spatial distribution and the intensity of COVID-19. In fact, the dominance of this factor has changed little; however, we see more evidence of spatial autocorrelation of COVID-19 data in the second half of the year. We found that spatial and temporal scale and improved resolution have uncovered disease patterns that can better inform decision-making at the local level. It is interesting to see how the proportion of studies that study COVID-19 on a global scale has fallen compared to the first half of 2020, from 30% to 7% of papers (Franch-Pardo et al., 2020). The geoenvironmental and socioeconomic dynamics play a statistically more important role in the distribution of diseases at more local levels. Not only that, but based on the health measures adopted by each country, there are very diverse spatial and temporal variations in behavior and response, strengthening the notion of mitigating the pandemic at the local levels where health-care systems typically operate.

For this reason, to facilitate the applicability of spatial analysis in decision-making, information must be collected and made available at high spatial and temporal resolution. Although it is also true that the latter can be discussed under the current issue of levels of violation of privacy for human security. It is an open debate.

However, the anonymous and detailed data sets allow the design of specific management strategies with greater possibilities of limiting the chains of infection. The probability of significantly reducing spread is further increased if high-resolution data are combined with field work (Ghilardi et al., 2020). While aggregated spatial data at the county or municipal level have utility at the state or national political scope, they offer an debatable utility to contain the pandemic in local perspective. To address this, many studies working at the city level use alternative data sources, such as VGI, mobility data, and RS to overcome this limiting factor (Tables 3–5).

TABLE 5 Volunteered geographic information

Study	Region or country of study	Variables used: Demographic and socioeconomic	Contamination	Weather	Mobility	Health services	COVID-19 data	Specific topics and analysis: Spatiotemporal analysis	Risk maps	Urban context	Political measures in research	Geographic specifications
Gorayeb et al. (2020)	Brazil	×				×	VGI		×	Fortaleza	×	Urban planning
Rossman et al. (2020)	Israel	×				×	Polls and confirmed cases		×		×	Territorial planning
Antoniou et al. (2020)	Greece	×				×	Crowdsourcing GIS		×		×	Territorial planning
Debnath and Bardhan (2020)	Turkey	×				×	Polls and confirmed cases		×		×	Territorial planning
Brito et al. (2020)	Brazil	×				×	Polls and confirmed cases		×	×	×	Territorial planning
Sandifer et al. (2020)	USA	×		×			Polls and remote sensing		×			Territorial planning
Leal-Neto, Santos, Lee, Albuquerque, and Souza (2020)	Brazil					×	Participatory surveillance testing and confirmed cases	×		Caruaru		Urban planning
Yoneoka et al. (2020)	Japan						VGI and confirmed cases	×		Tokyo		
Vannoni et al. (2020)	World				×			×		×	×	

Temporality regarding data access and information dissemination is the other main issue faced by the spatial epidemiology of COVID-19 when studies try to conduct real-time analysis of an ongoing pandemic. It is well known that there are lags in COVID-19 data reporting. Curtis et al. (2020) propose that COVID-19 data go directly from health systems and automatically to GIS platforms that can routinely monitor cases and deaths, due to the speed of transmission. Conversely, the publication process of peer-reviewed scientific articles can delay important findings. For example, research that studied the impacts of lockdowns were published in late 2020, when many nations had already relaxed COVID-19 public health measures that were implemented in the first half of 2020. However, retrospective studies are still valuable for improving public health preparation and response for current and future outbreaks.

The spatial analysis of COVID-19 also highlights important advances in technology for spatial and geographical science research, for example, the development and consolidation of new spatial analysis software such as GeoMEDD (Curtis et al., 2020) and OSMnx (Boeing, 2020); new models for risk estimation (Chatterjee et al., 2020; Mobaied, 2020; O'Sullivan et al., 2020; Sun, Di, et al., 2020); algorithms for the management of spatial big data (Buscema et al., 2020; Fang et al., 2020; Li, Li, et al., 2020; Shah & Patel, 2020); new clustering techniques and automated spatial statistics (Curtis et al., 2020; Fang et al., 2020; Melin et al., 2020); effective new forms of COVID-19 mapping on the web (Ghilardi et al., 2020; Graves & He, 2020; Maharjan et al., 2020); novel UAV applications (Okyere et al., 2020; Sahraoui, Korichi, Kerrache, Bilal, & Amadeo, 2020); and utilization of VGI (Hohl et al., 2020; Rossman et al., 2020; Yoneoka et al., 2020), among others.

Spatial statistical models are among the most widely used and thus could be considered among the most popular tools for studying the COVID-19 pandemic during the second half of 2020 (Figure 2). Spatial regression and autocorrelation as well as multicriteria analysis are found in the majority of GIS-based studies, although we found the study of socioeconomic variables to be more common compared to the first half of the year (Franch-Pardo et al., 2020). Specifically, there has been a substantial increase in the production of vulnerability maps of COVID-19 in urban environments.

There has also been an increase in studies using RS analysis. A majority of these studies have focused on air quality. In contrast, in the first half of 2020, analyses were more likely to focus on the climate and its relationship to COVID-19. In this regard, some studies affirm that the climate played a greater role in the first months of the pandemic, and that its impact has dissipated in later phases (Méndez-Arriaga, 2020).

Web mapping continues to be a principal medium for disseminating public information about COVID-19. Consistent with Chatterjee et al. (2020), public health organizations and governments recommend many preventive measures such as social distancing and personal hygiene, but one of the dominant strategies remains communicating risks and raising awareness to break chains of infection. Web maps provide a powerful means to influence these strategies.

Most spatial analyses use administrative boundaries as their units of study. From a global perspective, nation-states dictate the management of the pandemic since they control land, air, and water ports of entry, something that is decisive in times of crisis. For example, decreasing mobility via air traffic may decrease COVID-19 transmission by up to 90% (Foucher, 2020).

In this regard, another important objective in the reviewed papers has been to analyze how political decisions in each country have impacted populations at various spatial scales. The government decisions adopted explain a large part of the geographical changes that have occurred: the spatiotemporal evolution of the pandemic, pollution levels, mobility, and socioeconomic repercussions. Specifically, lockdowns were the most studied space-time phenomenon in the second half of 2020, something addressed by all disciplines that spatially analyze COVID-19. Not all countries implemented lockdowns, but, to a greater or lesser degree, all have reduced the mobility of their residents as well as their economic and production activities. Altogether, the other most studied event in this pandemic has been the Spring Festival of China in the first half of 2020 (Gan, Li, He, & Li, 2020; He et al., 2020; Tian et al., 2020; Tong et al., 2020; Yang et al., 2020).

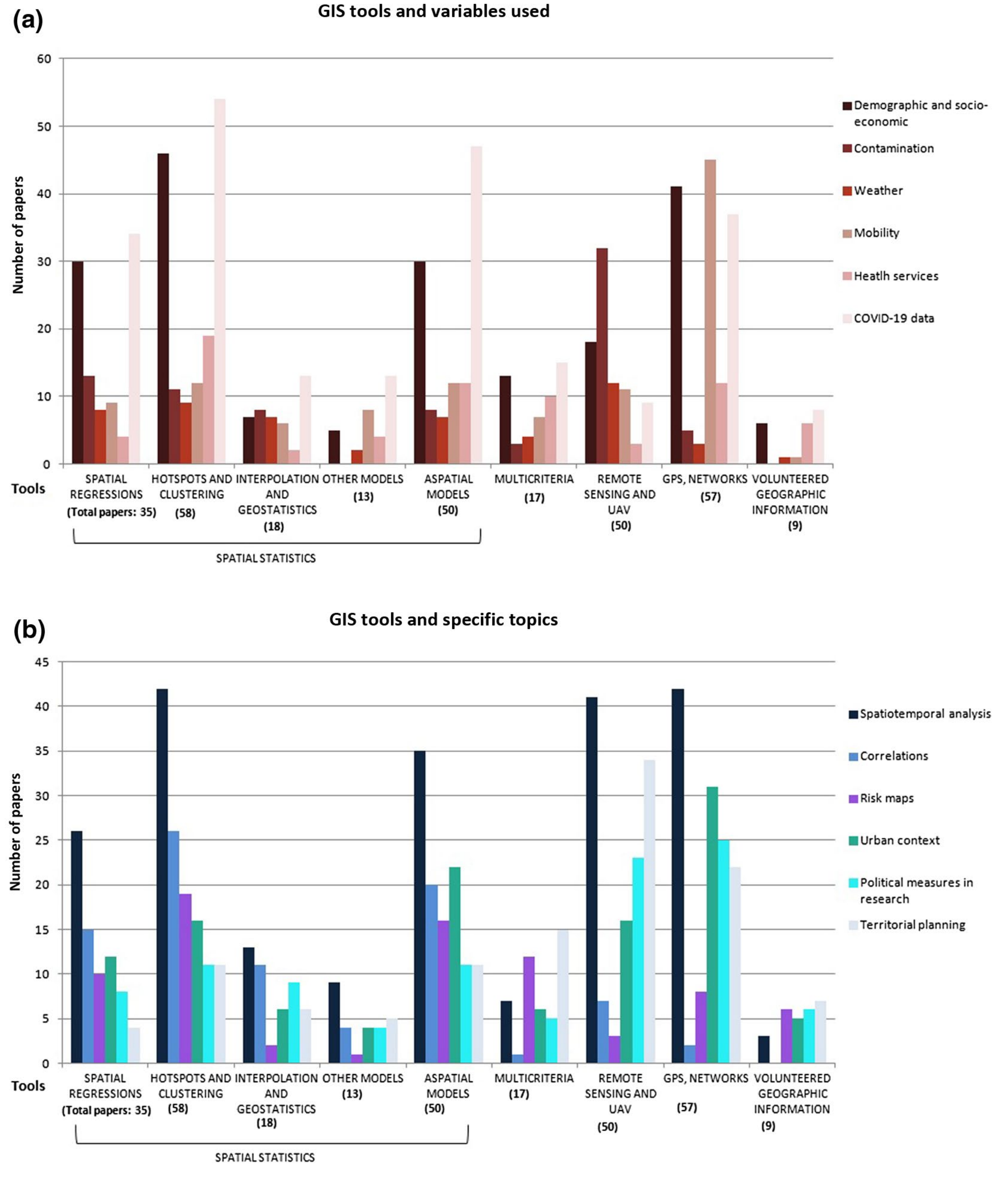

FIGURE 2 GIS tools and (a) variables used, (b) topics covered

On the other hand, COVID-19 transmission is higher in metropolitan areas, as discussed in the large number of reviewed works in urban environments around the world. The UN-Habitat report for the mitigation of the externalities based on SARS-CoV-2 in global cities corroborates other studies in urban environments. The report expresses concern that the pandemic will be most devastating in poor and densely populated urban areas (Mishra et al., 2020; UN Habitat, 2020). COVID-19 is also influenced by the notion of metabolic rift (Foster & Suwandi, 2020; Wallace, Liebman, Chaves, & Wallace, 2020), that is, in relation to the effects of geographical changes between rural and urban populations, associated with capitalism (Foster, 1999; Napoletano et al., 2019).

Following this argument, and although there are notable studies based in Ghana, Egypt, Morocco, Algeria, Nigeria, and Uganda, we observe a gap in contributions from Africa. In the second half of 2020, the majority of spatial analyses were conducted within the territories of China and the United States. In comparison with the previous 6 months, India accounted for the greatest increase in studies using spatial analysis, whereas global-scale studies have mostly declined. Finally, there seems to be a consistent amount of research coming from Brazil and Italy in the latest contributions.

5 | CONCLUSIONS

This work is a synthesis on the spatial analytical tools, their themes, and their fields of application on COVID-19. We hope this review provides new reflections and facilitates the development and improvement of spatial science methods to study COVID-19. GIS-related tools and techniques have served to monitor, evaluate situations, predict events, and inform policy decisions, all while the world has begun vaccination campaigns. We expect that the economic, societal, and environmental changes as a consequence of the evolution of the COVID-19 pandemic will influence the scientific world with new research strategies. However, new waves of the pandemic and the arrival of vaccines may result in a more uneven distribution of the impact of COVID-19. Spatial analysis and geography will continue to be powerful tools to understand and predict the evolution of the pandemic at a variety of spatial and spatiotemporal scales.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in [repository name e.g., "figshare"] at http://doi.org/[doi], reference number [reference number].

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