Spatial analysis tools to address the geographic dimension of COVID-19

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11.1 Introduction

Discussions of spatial analysis generally refer to the study of any information that includes a geographic dimension. In other words, it studies information that is spatially identifiable and, thus able to be mapped. This is independent of whether a given analysis is qualitative or quantitative.

The spatial analysis of geographic data with geographic information systems (GIS) seeks to describe, evaluate, and understand processes occurring in geographic space and possibly using that understanding to inform decision-making [1]. The GIS analyst incorporates co-incident variables and other subject matter in spatiotemporal models. GIS is an information system to capture, manage, manipulate, analyze, model, and represent geographic, spatial, and georeferenced data. By working with varied data layers, we can identify correlations between spatially distributed variables. In this work we highlight the diverse use of these tools for studying the COVID-19 pandemic.

Studies of the pandemic in the spheres of medicine, mathematics, social sciences, as well as interdisciplinary synergies include geographic

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components. The various geographic facets of these studies are addressed by the spatial analysis tools presented in this chapter.

The fields of medicine and health are not new to GIS [2–4]. In the midst of the COVID-19 global health crisis, health systems depend to a large extent on contact tracing to prevent COVID-19 propagation. Within this framework, GIS, and spatial analysis tools have been especially designed for the study and execution of nonpharmaceutical intervention strategies [5].

GIS has numerous uses specific to the field of public health [6–8]. It is used to monitor the epidemiological evolution of the disease and create explanatory maps for distribution and communication. It is involved in the spatial surveillance of the disease and rapid detection, understanding the dynamics of the pandemic, studying and controlling outbreaks, and for identifying problems of a spatial nature. It is used to improve public safety, such as by responding effectively to health emergencies, anticipating logistical needs and distributing resources, and strategizing policy measures. Furthermore, researchers use spatial analysis to contextualize and understand coincident variables and make predictive models.

Specific to this review, we highlight the spatial analysis tools (GIS, spatial statistics, remote sensing, GPS) that have seen the most use in addressing the COVID-19 pandemic. We focus on papers published in the second half of 2020. This allows us to compare with previous work including reviews or reflections on the utility of this technology for pandemic research [5–7,9–14]. Only months ago, due to logistics, novelty and lack of research, we had far less information. We have seen an enormous increase in publications related to the COVID-19 pandemic. In just a few months the number of studies using spatial analysis has greatly multiplied. To conduct this review, we consulted ScienceDirect, Web of Science, and Google Scholar, identifying 114 articles on the topics of COVID-19, GIS, spatial statistics and their specific tools, as are presented in the following pages. The order of appearance was determined based on the respective volume of work addressing COVID-19.

11.2 Spatial analysis tools

11.2.1 Spatial statistics in GIS for COVID-19

One of the most commonly used spatial analysis methods is ordinary least squares (OLS). OLS is a form of global multiple linear regression that minimizes the sum of squares of the vertical distances between the data values and those of the estimated model [15]. It indicates the strength and the average meaning of the independent variables [16] and, as such, is essentially one-size-fits-all [17]. It is has been used for analyses of socioeconomic variables [18–20], urban environments [17,21–23], and social vulnerability [24,25], among others.

Certain cases require refining a geographically weighted regression (GWR) model, using the variables previously included in the OLS regression. In the case of Karaye and Horney [24] , for example, this is caused by the nonstationary vulnerability to COVID-19 among U.S. counties.

GWR regression creates a local model and calculates the parameters for all points of the sample considering the spatial variation in the relationships [26,27]. It considers nonstationary variables (such as climate, demographic factors, and characters of the physical context) and models the local relationships between those predictors and the patterns under study. Although GWR is a useful exploratory technique, its utility as a predictive tool is controversial (Statistics solutions). It facilitates analysis of spatial variation in a phenomenon in a given place [28] , following Tobler's first law of geography (1970) that "everything is related to everything else, but near things are more related than distant things."

Murgante et al. [28] look for geographic parallels between affected areas in the valley region of Po and the metropolitan region of Wuhan. They find that both pollution and land use play important roles in explaining the distribution of COVID-19 in the two regions. Wu et al. [17] use GWR for each study site, basing the local regression on data from adjacent neighborhoods, thus estimating local regression coefficients for each of the predictor variables [16]. Mansour, Al Kindi, Al-Said, Al-Said, and Atkinson [29], in Oman, correlate sociodemographic variables with COVID-19.

Iyanda et al. [18] note that GWR has encountered recent critiques given its inability to address spatial multicolinearity, its inability to mitigate for spatial and atypical autocorrelation, and its bandwidth with a single core that fails to consider the size of geographic units. This last major weakness of GWR, which assumes that all the processes being modeled operate at the same spatial scale, lead to the development of multiscale geographically weighted regression (MGWR) [27,30]. The latter model allows different processes to operate at different spatial scales. Iyanda et al. [18] use MGWR with socio-demographic variables and out-of-pocket expenditure at the global level. Mollalo, Vahedi, and Rivera [31], on the other hand, use it for a local-level examination of the spatial nonstationarity between 35 environmental, socioeconomic, topographic, and demographic variables by U.S. counties. Likewise for European countries, Sannigrahi et al. [19] estimate local spatial correlation coefficients between socio-demographic variables and COVID-19 data.

Among generalized linear models, logistic regression has had special prominence in geographic studies of COVID-19. Poisson distribution describes the expected frequency of a set of probabilities for a discrete variable [32]. Each point of the distribution represents the probability that a given number of events occurs during a time period in a specific place or population. This distribution is typically used to study events with small probabilities or anomalous eventsDiaz Quijano [33].

To explore infection dynamics at the neighborhood level, Harris [34] analyzes differences in the number of COVID-19 deaths across borders of neighboring locations and looks for relationships with other differences in the make-up of neighbors. The assumption is that, all else being equal, nearby locations should have similar mortality levels because they share the same geographic context and because the infection is transmitted through close contact between people. Although based on a simple principle, when applied it induces a clustering effect in the data that is addressed through a multilevel Poisson model.

Yip et al. [23] use the Poisson distribution, among other regression, to evaluate the association between notified confirmed cases and the constructed environment in Hong Kong. Other significant uses of Poisson include studies by Andersen, Harden, Sugg, Runkle, and Lundquist [35], Desjardins et al. [36], and Hohl, Delmelle, Desjardins, and Lan [37]. Their surveillance studies assume that COVID-19 cases have a Poisson distribution and use that to infer high-risk geographic hotspots. Das et al. [38] use Poisson as well as other models to evaluate the impact of living environment in hotspots in the city of Kolkata (India), similar to Harris [34] in London. Sugg, Spaulding, and Lane [39] attempt to determine the driving factors in accumulated COVID-19 cases in nursing homes at local scales.

As can be seen, it is crucial to be able to detect hotspots. Hotspot identification allows a focused approach to assessment and response by local, state, and federal agencies. One of the most common tools to measure local clustering is the Getis-Ord Gi statistic [40] (e.g. [34,39,41–47]). The statistic is calculated by analyzing every entity within the context of neighboring entities. An entity with a high value is relevant, but it may not be a statistically significant hotspot. Following Tobler's first law (1970) [48], 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 [49].

For measuring spatial autocorrelation, Global Univariate Moran's is one of the most used methods (e. g. [17,18,20,28,43,46,50–54]. The global version, Moran's I evaluates the pattern and general tendency of the data. As a global indicator, it overlooks the instability of local spatial processes, which leads to the development of the local version of Moran [55] which identifies both the spatial clustering of entities with similar values and the occurrence of divergent values. This latter version is known as local indicators of spatial association (LISA).

Xie et al. [53] in China, Murgante et al. [28] in the United States, and Santana Juárez et al. [52] in Mexico create LISA cluster maps to analyze the characteristics of local spatial correlation of the COVID-19 epidemic. Wu et al. [17] use LISA to test whether the stationarity of the incidence

of COVID-19 in China. Sun, Di, Sprigg, Tong, and Casal [56] use LISA to map COVID-19 risk in the U.S. as well as to identify hotspots related to demographic variables. Mollalo et al. [46] examine the spatial pattern of mortality associated with lower respiratory tract infections and adjusted for age with global and local indices of spatial autocorrelation. They use the Moran's I and the Getis-Ord General G to investigate the extent to which nearby counties have similar rates of lower respiratory tract infections. Yao et al. (2020), analyzing 49 Chinese cities, investigate the associations between concentrations of particulate matter and the COVID-19 fatality rate. Sun et al. [56] use Moran to spatially relate the COVID-19 mortality rates with non-COVID-19 mortality in the United States.

11.2.2 Multicriteria analysis

Our review of correlation methods for multicriteria analysis highlights the importance of the Pearson correlation coefficient. The test statistic measures the strength of association between two continuous variables. It is considered the best method to measure the association between variable of interest because it is based on the covariance method. The statistic indicates the magnitude of correlation as well as the direction of the relationship (Statistics solutions).

Chatterjee et al. [57] measured variables relating social behavior with age groups, socio-political, exposure, and comorbidities. Mollalo et al. [31] use the Pearson correlation coefficient in a U.S. case study to investigate the correlations between socioeconomic, behavioral, environmental, topographic, and demographic variables. Wu et al. [17] use the same to evaluate the relationship between environmental variables and COVID-19. Bherwani, Anjum, and Kumar [58] study population, density, and area by state in India. Tao, Downs, Beckie, Chen, and McNelley [59] analyzed the Pearson coefficient for the correlation between population density and accessibility of COVID-19 testing sites. Using atmospheric data, Coccia [60] and Marquès, Rovira, Nadal, and Domingo [61] correlated atmospheric stability and stability of pollution levels.

While the Pearson coefficient evaluates the linear relationship between two continuous variables (a relationship is linear when a change in one variable is associated with a proportional change in the other variable), the Spearman and Kendall correlation evaluates the monotonic relationship between two continuous or ordinal variables, without considering the linearity of the relationship. Prunet, Lezeaux, Camy-Peyret, and Thevenon [62] use Spearman to extract the correlation between remotely sensed NO_2 data (S5P) and in situ NO_2 data. Pani, Lin, and RavindraBabu [63] correlate COVID-19 with meteorological parameters. Sun et al. [56], in the U.S.,

design a probability model to estimate the community risk of exposure to pandemics, which uses Spearman in different time intervals, as well as to study the relationship in estimation of risk between neighboring counties. Ran, Zhao, and Han [64] use Spearman to evaluate the relationship between the ozone and the spatial distribution of COVID-19 [62].

Analytic Hierarchy Process (AHP) is a multicriteria decision-making model [65]. 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 [66]. It is widely used for issues related to environment and health. Requia et al. [66], working in Brazil, establish a hierarchical network for issues of land use, socioeconomic, population, health conditions, and the healthcare system. Mishra et al. [67] use AHP to generate a COVID vulnerability index for urban environments in India and Fang et al. [45] perform a similar process for the island of Xiamén, China. Yao et al. [68] use multicriteria analysis to model the potential distribution of soya crops and how the soya trade has changed since the COVID-19 pandemic.

Following this account of interesting works, Wei, Liu, and Zhu [69] look at the intersection of meteorologic and transportation variables, factors that may play an important role in COVID-19 transmission in continental China. Their study shows that counties crossed by railroads or major highways or that have airports have significantly greater risk of COVID-19, and at the same time, they find that the greatest COVID-19 attack rates are significantly associated with lower average temperature, moderate cumulative precipitation, and greater wind speeds.

According to Karaye and Horney [24], it is essential to address social determinants of health, such as housing, education, and environmental and economic justice in order to reduce the inequities associated with health disasters in the U.S. As such, they use socio-economic, climatic, and PM2.5 data to show that the socio-economic conditions of the infected population profoundly affect the health of socially vulnerable communities. The study finds that minority status and language, household composition and disability, and housing and transportation can be used to predict COVID-19 case counts in U.S. counties. This is consistent with findings by Harris [34] for London neighborhoods. Karaye and Horney [24] position their analysis as further evidence that age, relative wealth, and ethnicity are key risk factors associated with the highest COVID-19 mortality rates. In a study also addressing socio-economic disparities, Cuadros, Xiao, and Mukandavire [70] develop a mathematic model to classify the population by Susceptible-Infected-Hospitalized-Recuperated-Dead (SIHRD).

11.2.3 Geostatistics

Geostatistics refers to a collection of spatial statistical tools and techniques to analyze and predict values of a continuous variable [71]. Here we focus on interpolation methods used for the analysis of COVID-19 spatiotemporal patterns.

Inverse distance weight (IDW) interpolation: Saha, Barman, and Chouhan [72] analyze the impact of the COVID-19 lockdown on community mobility by changing spatiotemporal series in different Indian states. They use IDW to show movement trends before and after the lockdown. They use data from COVID-19 community mobility reports from Google, 2020 to address the spatiotemporal dynamics centered on the social isolation policies, with the use of human mobility variables. Park, Jo, and Cho [73] use IDW to model the concentration of PM 2.5 in the city of Guro-gu (Seoul). Prunet et al. [62] use IDW to map S5P L2 NO2 data in a customized grid that allows them to calculate temporal averages while assuring that the results are equivalent for cities at different latitudes (Paris, Milan, Athens, and Madrid). Their use of IDW minimizes interpolation error by weighting measurements based on their proximity to interpolation points.

Another form of interpolation is kriging. The method is most commonly used for climatic variables [54,6869,74] and common atmospheric contaminants [50,64]. In the latter case, research has used kriging to identify associations between air pollution and COVID-19.

A related technique is cokriging. Kerimray, Baimatova, and Ibragimova [75] use cokriging to map distributions of PM 2.5 and benzene in Almaty in 2018–2019 and 2020, respectively. In particular, they are interested in the effect of government-mandated lockdowns on concentrations of these materials.

Finally, spline interpolations are another technique to use discrete data points to model a continuous variable. Sui, Zhang, and Shang [76] use cubic spline interpolation (CSI) to estimate the second-by-second speed of buses and taxis, using data from vehicle GPS devices.

11.2.4 Other models

Geographically Weighted Principal Component Analysis (GWPCA). GWPCA is an extension of the classic principal components analysis (PCA) that adapts the approach for use with geographic data by considering the spatial heterogeneity of the data [77]. Covariances are weighted based on the distance between the feature object and neighboring features. In essence, GWPCA performs a local PCA using the neighborhood surrounding each spatial feature [38]. Basu et al. [42] note that GWPCA does not

require additional data to weight the variables. It is successfully applied in a wide range of fields such as economic development modeling, deprivation, pollution sources, water resources, environmental health, soil characteristics, and landslides. Das et al. [38] use GWPCA in developing their improved Index of Multiple Deprivations (IMD) in districts of Calcutta, using housing condition, household amenities, water, sanitation, and hygiene (WaSH), asset possession, and gender disparity.

Voronoi: Bherwani et al. [58] use Bayesian probabilistic modeling to understand the relationship between COVID-19 cases and population density in a given region together with GIS-based Voronoi diagram to identify high-risk areas. Subsequently, Thiessen polygons delineate the risk zone boundaries.

Spatial autocorrelation from Clifford, Richardson, and Hemon [78]: Nomura, Yoneoka, and Shi [79], in the prefecture of Fukuoka, Japan, execute this spatial autocorrelation analysis 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 for these methods to structure epidemiological evaluation and assist in policy evaluations such as emergency declarations.

Spatial error model (SEM) and spatial lag model (SLM): Iyanda et al. [18]; Maiti et al. [27]; Mollalo et al. [31]; Sannigrahi et al. [19]; Sun et al. [20].

Spatial autoregressive combined (SAC): Sun et al. [20]; Zulkarnain and Ramadani [80]

Self-organizing maps (SOM), also referred to as Kohonen [81]

Spatial Markov [82]

Birthday paradox [56]

Topological Weighted Centroid (TWC) by Buscema, Della Torre, Breda, Massini, and Grossi [83], a new algorithm used in Italy

Space-time scan statistic from Kulldorff [84]: Andersen et al. [35]

Spatiotemporal refined risk model [85].

Geodetector: Wu et al., [17], Xie et al. [53].

Random forest: Kerimray et al. [75]; Mollalo et al. [46]; Pourghasemi, Pouyan, and Heidari [86].

11.2.5 Remote sensing (RS) and unmanned aerial vehicle (UAV)

By Earth's spheres (integrated biosphere):

The atmosphere:

The subject of relevant atmospheric analyses tends to fall into one of two categories: climatic conditions or pollution. Regarding the spatiotemporal dynamics of climatic conditions, these are analyzed at all scales

[17,54,63,87–92]. About spatiotemporal analyses of pollution levels during the pandemic, these tend to focus on the consequence of reductions in mobility and economic production [17,91,93,94]. There is special attention paid to countries that adopted lockdowns to control the pandemic, as well as to issues specifically affecting urban areas.

In the lithosphere:

Land use change, with significant examples such as the case of Yao et al. [68] where analyze the potential distribution of soya crops and how COVID-19 has affected the soya market. Brancalion et al. [95] look at a possibly faster pace of tropical deforestation during 2020. Wang, Peng, and Yu [96] conduct a land use analysis of crops in China to evaluate whether the pandemic led to increased cultivation and land exploitation; their findings are relevant for the development of agricultural policy to guarantee food security. RS and UAV also have applications for the real estate market as they are used for property inspection [97]

Analysis in urban environments associated with the level of pollutants they emit [38,62]. 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 [98].

Research on the dynamics of human movement during the pandemic demonstrates important applications of RS and UAV. Minetto, Segundo, Rotich, and Sarkar [99] 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 image time series will allow for temporal analysis of societal indicators [99]. Similarly, Wu et al. [17] 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, Chuku, and Ekumah [100] use UAV 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 [101]. Using RS and spatial models, the authors design the "Risk of Vulnerability to COVID-19 in War Zones Index" (Id_Covid19_WZ) to identify areas that are vulnerable to the pandemic and thus help decision-makers to limit risk and avoid and/or manage widespread infection.

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 are evaluated in both the Ganges River [102] and the Sabarmati River [103] in India using Lansat 8 and Sentinel-2 imagery, respectively. Similar methods are applied to measure lake pollution, such as by Yunus, Masago, and Hijioka [104] 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 (HAB) 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 at a time when in situ sampling was restricted by a mandated lockdown [105].

The tools are also highly relevant to topics related to ocean economic activities. For example, UAV was used in Ghana to monitoring water-based activity during COVID-19, in order to provide solid scientific evidence as a basis for decision-making in the artisanal fishing sector [100].

11.2.6 Participative GIS, mapping, voluntary geographic information (VGI), public participation GIS (PPGIS)

Green areas in the cities, nature, public spaces play an important role in times of crisis [106,107]. Public participation GIS (PPGIS) and Voluntary geographic information (VGI) are important tools, in addition to existing information sources, for gathering data from the population to fight COVID-19. Gorayeb, de Oliveira, and da Cunha [108] describes 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, with this, to follow up with infected persons over time [109]. 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 [110] and Turkey [111] 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 [110,112].

11.2.7 GPS networks

Throughout this overview, we have detailed numerous works employing GPS. In the following section, we focus on data mining and analysis of communication and transportation networks.

Studies using data mining to study human mobility tend to focus on areas where lockdowns were enacted. We differentiate these studies by their inputs: a) cellular telephone data [113–117, 74,118]; b) data from

Google, Facebook, Apple, and Baidu, and geotagged tweets from Twitter [119–125]; c) data from bicycle share systems in urban contexts [126] ; d) geo-tagged data from identified infections compiled into travel histories [127].

On the topic of transportation networks, we emphasize analyses of the movement or trajectory of the following: vessels during lockdown in Venice, Italy [128]; public transport and taxis in Qingdao, China [76] ; transportation in Milano, Italy [129].

Other studies are centered on highway networks in Jaipur, India [130] or in Tarragona province, Spain [131] , where there was a significant decline in capacity during the lockdown. Furthermore, Silalahi, Hidayat, Dewi, Purwono, and Oktaviani [132] for Jakarta, Indonesia, and Alasadi, Aziz, and Dhiya [133] for Basora, Iraq, provide important analyses of hospital accessibility.

11.2.8 Web mapping

Thanks to the availability of consistently-updated open data and to the availability of web cartographic templates, plugins, and shared code, there are many geospatial on-line platforms for monitoring COVID-19 around the world [134], which have emerged from organizations, academic institutions, or media organizations.

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 (UNAM) (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 titled Open Data 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 [134]. These geographic data are mapped and published through an ArcGIS Online web dashboard using the template created by Dong, Du, and Gardner [135].

In recent months, other notable graphics have been produced using cartograms to represent COVID-19 data world-wide [136], China [137,138], USA [139], and Europe [140].

11.3 Discussion and conclusions

During the first half of 2020, Tobler's first law of geography was not apparent in analyzing COVID-19 at a global scale. The disease evolution indicated by the constellation of the epicenters on the global map had more resemblance to Lévy flight [141], in other words randomly distributed, where human movement seemed to be the sole driving factor in the spatial distribution and intensity of COVID-19. In fact, the dominance of this factor has changed little, but, by reviewing the works from the second half of the year in combination as we have here, we see more evidence of Tobler's law. We find that cartographic scale and enhanced resolution of the units of analysis uncovers the role of geography in disease patterns. Physio-geographic dynamics have a greater role in disease distribution at more local levels. As such, to facilitate the applicability of spatial analysis to decision-making, information must be collected and made available with high spatial resolution. Detailed datasets allow the design of targeted management strategies with greater chances of limiting chains of infection. The likelihood of significantly reducing spread increases further if high resolution data is paired with fieldwork [134]. Whereas aggregated spatial information, even at the municipal level, often serves only anecdotally. Although it may be useful to inform the general public, it offers minimal utility in containing the pandemic. To address this, many studies working at the city level use alternative data sources, such as VGI, mobility data, and remote sensing to break through this limiting factor.

From anthropogenic, economic, and social perspectives, there are conclusions to be drawn related to Tobler's concentual umbrella [48]. In fact, spatial statistics models are among the most widely used and thus could be considered among the most commonly used tools for studying the COVID-19 pandemic during the second half of 2020. Spatial correlation and autocorrelation, and multicriteria analysis are used in the greatest number of GIS-based studies among all the disciplines studying the pandemic, although we find that socio-economic variables have become more common in relation to the body work when compared to the first half of the year [10]. Specifically there has been a significant increase in the production of vulnerability maps of COVID-19 and urban environments.

PR has also exhibited outstanding production. Air pollution thematic has concentrated the largest number of studies. On the other hand, in the previous semester, the main objective of analysis was the climate and its relationship with COVID-19. In this regard, some studies affirm that the climate played a greater role in the first phase of the pandemic, and that its impact has dissipated in the later phases [142].

Web mapping continues to be a principal medium for disseminating public information about COVID-19. Consistent with Chatterjee et al. [57], public health organizations and governments advise many preventive

measures such as social distancing and personal hygiene, but one of the dominant strategies remains communicating risks and generating consciousness to break chains of infection. Web maps provide an eloquent means to effect these strategies.

Spatiotemporal analysis of before and during lockdowns was the topic most developed in the second half of 2020. Although 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. In the geographic dimension of the pandemic, lockdown dynamics were among the most analyzed phenomena, studied by all the disciplines with spatial analyses of COVID-19.

As can be seen, most spatial analyzes use administrative boundaries as their units of studies. From a global perspective, nation-states dictate the management of the pandemic and borders become the land, air and water ports of entry, which fulfill a series of functions (legal, control, security, health) that are decisive in time of crisis: terrorist threats or armed conflict and, in 2020, a pandemic [143]. Mobility is determined by state power and, as the spread of the virus is dictated by the main axes of air transport, the stoppage of more than 90% of traffic is the first effect of this policy of interrupting chains of contagion [143].

On the other hand, the global pandemic is inherently metropolitan in character [67] as proven by the large number of reviewed works in urban environments around the world. The publication by the UN-Habitat of a Response Plan for the mitigation of the externalities based on SARS-CoV-2 in global cities is further evidence. The report expresses concern for the urban nature of the pandemic and thus highlights the role of cities in disease transmission [67].

In this second half of the year, the most spatial analyses are conducted within the territories of China and the U.S. In comparison with the previous six months [10], India accounted for the greatest increase in spatial analysis studies whereas global-scale studies have most declined. There continue to be many studies based in Brazil, Iran, and Italy. Although there are notable studies based in Egypt, Ghana, Morocco, Nigeria, and Oman, we observe a powerful gap in contributions for the whole of Africa, where there are still many unknowns to solve.

GIS has served to monitor, evaluate situations, predict events, and inform policy decisions, all while the global populace awaits a vaccine. We expect that the economic dynamics and study topics will once again change in 2021, especially as vaccines begin to be administered and induce further changes around the globe.

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Non-Print Items

Abstract

Discussions of spatial analysis generally refer to the study of any information that includes a geographic dimension. In other words, it studies information that is spatially identifiable and, thus able to be mapped. This is independent of whether a given analysis is qualitative or quantitative.