Geospatial Analysis and Mapping Strategies for Fine Grained and Detailed COVID-19 Data With Geographic Information Systems

ÁNGEL MIRAMONTES CARBALLADA (✉ angel.miramontes@usc.es)

University of Santiago de Compostela: Universidade de Santiago de Compostela

<https://orcid.org/0000-0003-1162-3329>

JOSE BALSA-BARREIRO

MIT Media Lab

Research

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Geospatial analysis and mapping strategies for fine-grained and detailed COVID-19 data with Geographic Information Systems

Miramontes Carballada, A.¹ and Balsa-Barreiro, J.^{1,2}

¹Galician Studies and Development Institute (IDEGA), University of Santiago de Compostela, 15782 Santiago de Compostela (Spain)

²MIT Media Lab, 75 Amherst St, Cambridge, MA 02139, United States

Abstract

The CoVID-19 pandemic is showing a dramatic impact across the world. To the tragedy of the loss of human lives, we must add the great uncertainty that the new coronavirus is causing to our lives. Governments and public health authorities must be able to respond this emergency by taking the appropriate decisions for minimizing the impact of the virus. In the absence of an immediate solution, governments concentrate their efforts on adopting non-pharmaceutical interventions for restricting the mobility of people and reducing the social contact. Health authorities are doing public most of data that support their interventions and policies.

The geographic location of the cases is a vital information with exceptional value for analysing the spatio-temporal behaviour of the virus, doing feasible to anticipate potential outbreaks and to elaborate predictive risk mapping. In fact, a great number of media reports, research papers, and web-browsers have presented the COVID-19 disease spreading by using maps. However, processing and visualization of this sort of data presents some aspects that must be carefully reviewed. Based on our experience with fine-grained and detailed data related to COVID-19 in a Spanish region, we present a bunch of mapping strategies and good practices using geospatial tools. The ultimate goal is to create appropriate maps at any spatial scale while avoiding conflicts with data such as those related to patients' privacy.

Keywords

SARS-CoV-2, CoVID-19, Geographic Information Systems, spatial patterns, territorial impact, mapping

1. Introduction

On 31st December 2019, China reported a cluster of cases of pneumonia related to a novel coronavirus in the city of Wuhan in Hubei, mainland China. Twelve weeks later, on 11th March 2020, the World Health Organization (WHO) declared a global pandemic originated by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), aka the novel coronavirus 2019-nCoV. Today, more than one year later, the virus has spread uncontrollably around the world, despite all the mitigation strategies adopted by countries. As of 15th November, 63.9M confirmed cases and 1.3M deaths had been reported. In addition, the impact of the pandemic foreshadows difficult

economic scenarios [1], being expected an impoverishment of large sections of communities and a substantial increase in social inequalities at all levels [2,3].

The spread of the virus is explained by our individual and social behaviour. Many countries, especially the western ones, are having serious difficulties in containing the virus efficiently. The decisions adopted by these countries face a complicated trade-off between to constrain the individual freedom for moving from place to place and to preserve economic activities. National strategies range from coexistence with the virus to its suppression (i.e., Zero COVID), being referent the policies adopted by Sweden during the first wave and China.

Whatever the strategy adopted, the management of the pandemic has demonstrated the need to manage mobility flows. The final objective is to reduce transmission, especially in vulnerable groups of people, and optimize health resources until a potential vaccine or any other intervention potentially successful could reduce the impact of the pandemic.

Any action or intervention against the virus requires knowing its spatio-temporal behaviour. For this, it is necessary to anticipate the emergence of new outbreaks. In case of new infected people, fast tracking of their movements and contact tracing is required for controlling the potential spread of the virus. This process requires a fast and agile data management, taking into account the incubation period of the virus (up to 14 days) and the relatively high percentage of asymptomatic patients.

For addressing this emergency, governmental authorities and health managers establish special protocols for sharing sensitive data in order to take decisions based on scientific criteria. The geographical component of information (geodata) has become one of the most valued data for understanding how the virus spreads across the territory. The use of *Geographic Information Systems* (GIS) for mapping data may play a crucial role for fighting against infectious diseases such as COVID-19 covering aspects in different steps related with the territorial impact of the pandemic such the virus spreading, the contact tracing or the vaccine distribution, among others.

These GIS systems can help to support authorities and policy makers in the implementation of interventions against the virus.

There are more examples related with the importance of geospatial technologies during this pandemic. The proliferation of web mapping applications and dashboards has become a pivotal source of information during the COVID-19 pandemic, thanks to the combination of advanced computer graphics and technologically innovative imaging solutions [4]. The dynamic representation of information using these systems serves to inform and raise awareness in society, as well as helping to manage uncertainty, while improving the governments and authorities communication transparency. Mapping COVID-19 data in (near)-real time allows delimiting risk areas, in addition to reduce the risk of exposure to the virus and support authorities in decision-making. The most popular dashboards are the published by the *Center for Systems Science and Engineering at Johns Hopkins University* [5] and the *World Health Organization* [6]. Both dashboards represent official data for countries and regions in near-real time (approx. every 15 min). Another dashboard, HealthMap [7], uses online media data sources for real-time surveillance with a higher level of spatial resolution in some countries..The importance of geolocation technologies goes beyond. These may potentially be used for other virus-related tasks such optimised placing for emergency treatment units and basic resources in critical situations, enabling to ensure the supply chain and distribution of equipment and resources [8]. China and other countries have also used drones for logistics distribution or surveillance tasks during the pandemic, especially at times when it has been necessary to reduce human contact [9]. Integrated drone and GIS technologies allow to optimize efforts especially in those areas that need it most. This is particularly important in urban areas due to the high concentration of people and features, which increases the levels of risk. In these areas, it is required a very detailed mapping based on high-precision three-dimensional models [10].

Web app/platforms for tracking people allows to estimate mobility of infected and vulnerable people in each moment. Thus, it is possible to rebuild spatial patterns of the virus and to propose

adequate interventions for risk mitigation. Many countries have developed their own web app/platforms although with different success rates such as *Close Contact Detector* in China [11], *Trace Together* in Singapore [12], *COCOA* in Japan [13], *SwissCoVID* in Switzerland [14] or *RadarCoVID* in Spain [15].

All the previous examples show the importance of spatial analysis methods to understand the disease spread process, enabling to identify new outbreaks and spatial patterns. In addition, these allow to combine these data with the sociodemographic and environmental characteristics of the territory, achieving a holistic perspective of the actual impact of the disease [16]. Thus, it is possible to anticipate the future behaviour by developing models for predictive risk mapping based on computerised spatial analyses that integrate different calculation algorithms [17].

Paradoxically, the COVID-19 has become a great opportunity for the development and implementation of geospatial analysis for decision-making in emergencies [18]. The exponential increase in computing capacity for information processing, especially within GIS tools, is substantially improving our response capacity to emergencies like the current one. However, in the face of this boom of geospatial analysis, certain shortcomings related to the implementation of adequate strategies for mapping and processing geodata must be analysed.

The case study presented here is carried out in the region of Galicia, located in NW Spain. Precisely, Spain is one of the worst severely affected countries by the COVID-19. At a global scale, Spain is one of the most affected countries by COVID-19 (see Section 4.1). The sub-optimal national response to the COVID-19 pandemic has been widely criticized by relevant health management leaders and experts at a national scale [19]. In subsequent editorials of *The Lancet*, this group of leaders and scientists referred to the weakness of the so-called *test-trace-isolate* *tryptic* for explaining the imminent impact of the second wave. They made an urgent appeal to the authorities to publish accurate and detailed data on the virus' incidence [20, 21], which would facilitate the better understanding of the virus and to respond adequately to new outbreaks.

This case study counts with accurate and detailed fine-grained data related to all the officially registered cases of COVID-19 in the region of Galicia. These data include the residential address of each case, being possible to display our data at the highest spatial scale. Our objective with these data is to raise and to analyze adequate mapping strategies for enhancing the data value while avoiding conflicts and deficiencies related with the use of these data. The most important aspects related are presented and discussed later.

This paper is structured as follows. Section 2 provides a comprehensive literature review on how mapping has been used in the study of infectious diseases in the past and is being used in the current pandemic. Section 3 presents the work methodology. Section 4 introduces the study area and describes the dataset. Section 5 presents some visual results in form of maps. Section 6 discusses the previous results and other relevant aspects related to this research. Finally, we summarize the most relevant points presented in this paper.

2. Literature Review

Throughout human history, emerging and re-emerging infectious diseases threaten humankind. These diseases can transform themselves in epidemics when the rapid spread of disease to a large number of people in a given population within a short time lapses. Spatial spread depends on the disease mechanism, human mobility, and control strategy [22]. Understanding their high spatio-temporal behavior requires an exhaustive observation of their spatial patterns, which are due to a complex set of interactions between human and environmental factors [23], showing large regional differences.

The territorial factors behind the impact of diseases presents a tradition within the *health geography*. According to Kearns and Moon [24], this sub-discipline presents a predominantly utilitarian perspective by analyzing the territory technically, although it incorporates structuralist approaches, such as cultural and sociological vision of social welfare, a sense of place for people, and a critical stance. In recent decades, it is more frequent the compilation of maps for assessing

the territorial impact of certain diseases. Examples are the *Atlas of Cancer Mortality* in China [25] and in the United States [26]. These studies display incidence data, while other ones that are more recent are focused on determining levels of risk or identifying spatial patterns [27]. As examples, Castronovo, Chui and Naumova [28] analyzed the spatio-temporal dynamics of salmonella infections for 2002 in elderly people in the United States, while Mohd, Jacobsen and Wiersma [29] established risk maps of hepatitis A virus at a global scale.

Maps have become essential tools for understanding and tracking infectious diseases. One of the first infectious disease maps was carried out in 1694 on plague containment in southern Italy [30]. Although probably, the notorious John Snow's map on the 1854 cholera outbreak in London is the best known example to illustrate the power of mapping in public health [31]. There is a large recent literature regarding studies on mapping and spatial patterns of infectious diseases. A 2014 review of the health GIS literature found that 248 out of 865 focused on infectious disease mapping [32]. Wahid et al. [33] analyzed the spatial spread of the Chikungunya virus, a mosquito-transmitted alphavirus, since the first was reported in Tanzania in 1952. It has since spread across the entire globe causing large numbers of epidemics that have infected millions of people in Asia, India, Europe, the Americas, and Pacific Islands. Pigott et al. [34] assembled location data on all recorded zoonotic transmission to humans and Ebola virus infection in bats and primates since 1976 to 2014, predicting a transmission niche in different countries across Central and West Africa. Their study showed how despite 22 million people inhabit regions at risk, the rarity of human outbreaks emphasizes the very low probability of transmission to humans. Cattarino et al. [35] developed a high-resolution global map on the intensity of dengue spread by adapting geospatial models based on the environment. Samy et al. [36] studied the recent outbreaks of Zika, a new virus discovered in Uganda in 1947 that is transmitted by aedes mosquitoes. They studied spatial spread of Zika in South America, addressing urgent knowledge gaps regarding drivers of transmission and the global potential for spread this virus. Messina et al. [37] showed how large portions of tropical and sub-tropical regions globally have suitable environmental

conditions for the Zika virus with over 2.17 billion people inhabiting these areas. The list is much more extensive, with a bunch of studies analyzing the impact of other viruses in certain regions. Reeves, Samy and Peterson [38] carried out a first detailed geographic and environmental study of MERS-CoV distributions across the Middle East, Deka and Morshed [39] analyzed the spatial spread of Nipah virus in South and Southeast Asia, while Sánchez-Gomez et al. [40] did the same with West Nile virus in Spain.

The complexity of human and environmental interactions explains the magnitude of epidemics. GIS tools and the estimation of spatial statistics may help mitigate the epidemic through scientific information, finding spatial correlations with other variables and identifying transmission dynamics [41,42]. GIS tools favors a dynamic mapping based on simultaneous visualization of temporal and spatial information, enabling to evaluate the complex interactions between humans and environment [28]. To cite only a few examples, Grantz et al. [43] showed how living in census tracts with higher illiteracy rates increased the risk of influenza and pneumonia mortality during the influenza pandemic of 1918 in Chicago. Allcott et al. [44] evaluated the relationship between COVID-19 reported cases and the compliance level to containment measures against the virus in American counties. The recent implementation of GIS for disease mapping and correlated factor is detailed in some recent studies. Parks, MacDonald and Beiko [45] used an automated pipeline to collect data for analysis in the geospatial package *GenGIS*, which allows the geographic and temporal tracking of new sequence types and polymorphisms related to 2009 swine-origin strain of *influenza A (H1N1)*. Giyonko et al. [46] analyzed the epidemiological role of camels in the transmission of MERS-CoV virus by implementing an iterative empirical process in GIS to identify and qualify potential hotspots for maintenance and circulation of this virus. Fuller et al. [47] identified those areas where reassortment events might occur and how high pathogenicity Avian Influenza virus might travel if it enters wild bird populations in the United States.

Similarly, geospatial tools are already playing a key role in the current COVID-19 pandemic. These are used for aggregating big data from multiple sources, intuitive visualizations and maps,

spatially tracking confirmed cases, predicting regional transmission, balancing and managing supply and demand for material resources, which provided strong spatial information support for decision making, formulating measures and evaluating the effectiveness of prevention and control of COVID-19 cases [48]. Some recent studies evaluate the territorial impact of COVID-19 at different spatial scales [49,50]. A cross-sectional approach shows an association between the accelerated diffusion of the virus and high air pollution and low wind speeds [51]. Oto-Peralías [52] conducted a multifaceted study by combining geographical and socio-economic variables to explain the large disparity of infected people between Spanish provinces. He found interesting correlations with temperature and distance from Madrid, the capital city, during the first wave. The importance of the spatial dimension for disease mapping forces us to rethink certain relevant aspects to display cartographic information. In this regard, Cicalò and Valentino [4] introduced new approaches aimed to visualize, describe and explain spatial patterns of diseases. One of the most critical aspects is to define a scientific geographic unit for health-care market for analysis and visualization [53]. It will depend on the spatial scale and the level of aggregation of data. Thus, in the past it was more frequent to constrain to nearby environments. Tuckel et al. [54] studied the diffusion of the Influenza pandemic of 1918 in Hartford, Connecticut, United States, while Smallman-Raynor, Johnson and Cliff [55] did the same in London and the county boroughs of England and Wales. Nowadays, some studies limit the scope to much reduced events such as Rodriguez-Morales et al. [56], which studied a recent Zika virus outbreak in Valle de Cauca, Colombia. Nowadays, the high computational capacity of GIS tools makes it possible to expand the study to all spatial scales. The first studies about COVID-19 were conducted at national scale, although over time was more possible to carry out studies at more spatial scales (such counties or provinces), but always with aggregated data.

3. Methodology

We represent fine-grained health data associated with COVID-19 in the Spanish region of Galicia. These data contain individual and precise information on each case, including its residence address. It allowed to achieve a very accurate picture of the virus' spread within this region. These data were provided by regional health authorities in order to reach a better understanding of the spatial behaviour of the virus and to implement the adequate interventions for minimizing the impact derived.

In this paper, our objective is to raise different mapping strategies potentially valid for health management authorities. Maps may be used as crucial tools for identifying spatial patterns of the virus, constraining the virus, but also for checking if the interventions and policies adopted are working. Different mapping strategies are proposed by considering the multiscalability of data, the level of aggregation of data, and data privacy's concerns.

The strategies and methodologies for mapping these data must be valid for promoting the integration of multidisciplinary working teams, including professionals without any expertise in cartography. The potential of our results must facilitate the review, analysis, and interpretation of data enabling to identify potential risks and to take informed decisions by policymakers and authorities.

4. Data and study area

Here below our study area and the data used are presented. For this, this section is organized as follows. Initially, sub-section 4.1 contextualizes the impact of the pandemic at a national scale. Sub-section 4.2 introduces our study area based on two aspects: (a) its sociodemographic reality and (b) the impact of the pandemic according to the official statistics at a regional scale. Finally, our dataset is presented in sub-section 4.3. Incidence data related to COVID-19 are obtained from officially responsible institutions at national [57] and regional [58] scale.

4.1. The Spanish context

The novel coronavirus 2019-nCoV entered Spain on 31st January 2020, although no community spread was detected until early March. On 14th March the national authorities imposed a harsh lockdown with hard mobility restrictions and a forced halt to most labour activities. At that time, Spain counted 6,332 infected cases and 193 deaths. The lockdown lasted 49 days, followed by 48 days in which most of restrictions were progressively eased until the end of the first wave. The balance of this first wave, as of 21st June, was 246,504 infected cases and 28,313 deaths. Sadly, Spain is one of the most affected countries in the world. It was European country in living a second wave, counting a high number of cases in late summer. As of 15th November, Spain counted with 1.44 million reported cases, about 80,000 of them health-care workers. The number of deaths caused by the virus stands at 40,460, about 22,300 of them in nursing homes. Spain is the 6th country with more reported cases and the 9th country with more deaths at a global scale. It shows a fatality ratio of 2.8 deaths every 100 confirmed cases and 86.6 deaths per 100,000 inhabitants, one of the highest in the world after Belgium (121.6) and Peru (109.51). But these data could be even worse. According with the tables reporting excess mortality [59], actual number of deaths could be a third higher [60]. The seroprevalence studies carried out during the first wave, between 27th April and 11th May, estimated that only 5% of Spaniards had suffered the disease. These studies demonstrated substantial geographical variability, with higher prevalence around Madrid (> 10%) and lower in coastal areas (<3%) [61].

Figure 1. Number of reported cases and deaths from CoVID-19 in Spain since the beginning of the pandemic (31st January) until 15th November. Reported cases are shown in blue (Y-axis) and deaths in red (Y-axis inverted).

4.2. Our case study area: The region of Galicia

Firstly, we present our study area by describing its sociodemographic reality (4.2.a). It will give us some important insights related to the spatial pattern of the virus. After that, we will check the impact of the pandemic according to the officially reported numbers (4.2.b).

A) Geographical context

Our study area corresponds to the region of Galicia, which is located in northwestern Spain. This region has a population of 2.7 million inhabitants (6.1 percent of the Spanish population) and an area of 29,575 km² (5.8 percent of the Spanish area). Its population density is 91.3 inhabitants per square kilometre [62]. It is administratively divided into four provinces, and 313 municipalities, which correspond to local government units (third level of administration).

This region is characterised by the high dissemination of its population throughout the territory. In fact, around half of the human settlements in Spain are located in this region, which is around eight times more comparatively than its demographic weight at a national level [63]. In the last few decades, its traditional population model is in crisis, with more people living in a very reduced number of towns or cities. Nowadays, most of its population live next to the so-called *Atlantic Axis*,

where the major and most thriving cities are located. Five of the seven main cities of this region are located along this axis. Vigo and A Coruña are the two most important cities in the region with approximately 300,000 inhabitants. The rest of the major cities concentrates around 100,000 inhabitants, with the exception of Pontevedra and Ferrol, which are less populated. From an urban perspective, Galician region barely had intermediate urban referents with population between 30,000 and 100,000 inhabitants. However, in very recent years, some municipalities located in the suburban area of the most important cities (such as Narón, Arteixo, Ames, etc.) together with the decline of some traditional cities (Ferrol) has led to a recent emergence of an increasingly numerous group of intermediate cities.

The urban structure of this region is hierarchically dominated by the western part. Except for some rare cases, with some exceptions [64], this area presents positive demographic patterns both from a quantitative (higher rates of fertility, positive migratory balances) and a qualitative (less aged population) perspective. The opposite trends are observed in the eastern part where the two main urban referents concentrate a large part of the socioeconomic activity of their whole provinces. The rest of the territory is dominated by a group of head towns, with a great influence in large rural areas.

Figure 2. (a) The region of Galicia within Spain. The four background colours corresponds to provinces. The nodes in yellow, labelled with their respective names, represent the seven main cities. In this figure, it is also represented the main road networks, i.e. motorways/highways (red lines) and railways (yellow lines). (b) The sample study areas analyzed in section 5 are located and bounded by the red boxes.

B) Incidence of CoVID-19

As of 15th November, Galicia reported 43,714 cases, 5,783 hospitalised, 661 attended in intensive care units, and 1,084 deaths by COVID-19. Comparatively, these data represent 2.9% of the cases and 2.6% of the deaths registered in Spain. The ratio of cases per 100,000 inhabitants is 161.9, and 4 deaths per 100,000 inhabitants. The fatality rate is 2.5 deaths per 100 reported cases and 40.1 deaths per 100,000 inhabitants.

The results of the first wave, on 15th June, showed a total of 10,489 infections and 619 deaths.

The fatality rate was 5.9 deaths per 100 reported cases and 22.3 deaths per 100,000 inhabitants.

The seroprevalence study carried out by the Galician government during the first wave estimated that only 1.15% of its population had been infected, being one of the least affected regions in Spain.

Figure 3. Number of reported cases and deaths from CoVID-19 in Spain since the beginning of the pandemic (31st January) until 15th November. Reported cases are shown in blue (Y-axis) and deaths in red (Y-axis inverted).

4.3. Data

The dataset we will work on corresponds to all the individual cases reported in this region during the first wave of the pandemic, ranging between 1st March and 15th July, 2020. This dataset includes information related to all the cases officially reported by the *Galician Health Service* (SERGAS), the health management authority in this region. This dataset counts with 11,070 records, 581 more cases than those officially published. This excess data amount mostly corresponds with false positives.

Among the information included in the dataset, we count with bio data, place of residence, relevant dates, and some indicators that allows to check a complete follow-up of the disease for each reported case (i.e. home bound/hospital admission/death). Given that mobility was mostly restricted by the lockdown, the great majority of cases can be we can spatially and temporally delimited because dates related to symptoms and testing were recorded by the health workers. The place of residence for each reported case is defined by its official address, which allow us to obtain a very accurate representation of the spatial behaviour of the virus.

5. Results

The first step was to apply a pre-processing of data in order to eliminate wrong and duplicate data and adapt the structure and format of all the data. After that, we georeference the whole dataset using the API tool implemented in the software *ArcGis*. Each record is represented as a point entity that is spatially located based on the address field. In short, 10,853 records were located, which corresponds to the 98 percent of total.

Mapping addresses by dots give us a good approach to understand the spatial patterns drawn by the virus in this region. Most of these dots are concentrated close to the most important cities, especially along the Atlantic shoreline (Figure 4.a). Depending on the scale, the interpolation of these points in a raster map may facilitate a clearer and more intuitive identification of these spatial patterns. Figure 4.b shows a heat map where the point density is represented. The red-coloured areas represent the most affected areas by the virus, while the green-coloured areas the least ones. The degradation between the previous colours (i.e., mostly yellow tones) represents those areas with an intermediate level of cases.

Figure 4. Mapping COVID-19 cases officially reported in this region. (a) Representation of the most fine-grained level of detail. In this map, each single red dot corresponds to a reported

case, which is spatially located based on the private address. (b) Mapping using a heat map, where areas with the highest point densities corresponds to the areas in red. Raster composed of 358 columns and 323 rows, with a cell size 1000 x 1000.

A more detailed approach to the virus spreading is computing some relevant rates. This sort of rates is represented by choropleth maps, where each region is colour-shaded according to different value intervals. We estimate the density COVID-19 cases in relation to total population and total surface. Figure 5.a represents the number of COVID-19 cases per inhabitant, while Figure 5.b represents the number of COVID-19 cases per square kilometre. Both figures are choropleth maps where both rates are aggregately represented, in this case at a municipality level.

Figure 5. Mapping COVID-19 cases officially reported at a local scale of aggregation (municipalities). (a) Number of cases per 100,000 inhabitants. (b) Number of cases per 100 km². In both cases, the intervals are distributed in regular quartiles.

The COVID-19 cases' density by surface presents a very similar spatial pattern to the previous figures, where municipalities with a higher density of reported cases are located along the *Atlantic Axis*. However, the map of density of reported cases by population shows a spatial pattern quite

different. We can observe some groups of municipalities in the inner region showing the highest values for the whole region. In addition, we are able to clearly distinguish in both maps how some large areas were not affected at all by the virus. In fact, 18 municipalities (5.7 percent of the total), mostly located in the eastern part, did not report any case.

The complexity of the territory explains why COVID-19 cases' distribution is spatially heterogeneous. Thus, we must analyze data at multiples spatial scales, as shown below. Figure 6.1.a represents the spatial distribution of reported cases at a municipal level. This figure allows to discern a clear dichotomy between the municipalities located at the western and eastern sectors. However, zooming into the map we can observe how this spatial pattern is clearly fractal. Figure 6.1.b corresponds a small selection of the municipalities surrounding Vigo, the most populated city in this region with about 300,000 inhabitants. This area is located in the southern coast and it corresponds to the study area A in Figure 2.b. According to the map legend, all these municipalities were one of the most affected by COVID-19 at a regional scale.

Figure 6.2.a represents an internal distribution of reported cases at a lower level of spatial aggregation for the municipality of Vigo. This aggregation level corresponds to census districts. In total, the municipality of Vigo holds 236 census districts, whose size varies substantially depending on factors such as the resident population. The smallest census districts are located in the consolidated urban area, while the largest ones are located on the periphery. From the perspective of the virus spreading, we can refer to some relevant aspects. The majority of the most affected districts (red-coloured in the map) are located in the city area. But not all of them are located in the downtown, where theoretically the number of social interactions is higher. A relevant number of the red-coloured polygons corresponds to residential land uses, where the virus spreads mostly in familiar environments. The dichotomy between centre and periphery is more or less evident depending on the zoom view. Ten census districts in this municipality did not report any COVID-19 case, paradoxically some of these districts located close to the downtown. A more detailed view of the spatial distribution of cases in this city is visible in the following figures,

where we can compare two ways for mapping the spatial distribution of the virus: aggregated representation of the cases by census districts (Figure 6.2.b) or disaggregated representation of the cases in dots (Figure 6.2.c).

Figure 6.1. Number of CoVID-19 cases officially reported at a local scale of aggregation (municipalities). (a) Mapping data for the whole region. (b) Mapping data for a small case study located in the region of Vigo. Value intervals are distributed in regular quartiles.

(a)

(b)

(c)

Figure 6.2. (a) Number of COVID-19 cases officially reported at an intermediate scale of aggregation (census districts) in the municipality of Vigo. Value intervals are distributed in regular quartiles. (b) Zooming into a specific area in the downtown of Vigo. (c) Disaggregated representation of reported cases in the same area.

A problem of choropleth maps is that the values subscribe to specific areas, showing sharp boundaries between polygons. This can generate a biased visual perception of the represented phenomenon [65]. Risk delimitation per area may arbitrarily change depending on both the level of data aggregation and the geometric entity used for mapping. Figure 7 represents the density of COVID-19 cases in a specific area of A Coruña, the second most populated city in this region with about 250,000 inhabitants (study area B in Figure 2.b). The sample area represented is located to the south and covers an area of 0.21 square kilometres (Figure 7.a). The urban physiognomy of this area is structured from a dense street network. It is dominated by buildings of about five floors high. Although the layout of the streets is mostly rectilinear, the urban fabric is irregular and lacking in orthogonality. In addition, there is a general lack of green spaces. The COVID-19 cases are aggregately represented in street sections. In this way, we establish a zoning of the public space according to the risk levels. Two short street sections, symbolised in red and in a wider line, are those that concentrate more cases. In 91 of 130 street sections, symbolised in white and with a lower thickness, no cases were registered.

Figure 7. Number of COVID-19 cases officially reported in a specific area of A Coruña. (a) In yellow, we represent the location of this sample area within the city. (b) Data mapping of reported cases at the lowest scale of aggregation (street sections).

The disaggregated representation of the data in single nodes allows to achieve the maximum level of detail and spatial resolution. However, this sort of representation has certain disadvantages, especially when we manage sensitive data due to privacy concerns. Figure 8 represents three sample areas with different territorial typologies: urban, semi-urban, and rural. The first sub-image, Figure 8.a, represents a random sample area located in downtown of Santiago de Compostela, the capital of the region (study area C in Figure 2.b). This part of the city presents an urban structure of open blocks with large patios. It is comprised of narrow streets with a rectilinear layout and tall buildings, over five floors high. Figure 8.b corresponds to the centre of a middle town. Santa Comba (study area D in Figure 2.b). This town has about 3,000 inhabitants, but it is the most important urban referent for its municipality, with a population of about 10,000 inhabitants. The urban planning of this nucleus is characterised by an orthogonal

448 layout and a dense use of urban space, with buildings of variable height, from one to six floors
449 high [64]. Finally, Figure 8.c corresponds to a distinctly rural area located somewhere in the north
450 of the region. This small village has a concentrated physiognomy of a few mainly ground-floor
451 houses. Disaggregated mapping of COVID-19 cases by representing the personal addresses in
452 form of dots must be never carried out in eminently rural environments nor, in many cases, in
453 semi-urban ones since it is not clear whether the anonymity and privacy of those affected can be
454 guaranteed. Therefore, it is necessary to propose effective and responsible mapping strategies
455 adapted to each zoom factor and spatial scale.

(a)

(b)

(c)

Figure 8. Location of COVID-19 cases in different sample areas: (a) A specific area in the downtown of the city of Santiago de Compostela, (b) the centre of a head town located in the northwestern part of the region, and (c) s small village of undetermined location by privacy concerns.

461 The disaggregated representation of COVID-19 cases in dots may confuse the identification and
462 extraction of spatial patterns at some spatio-temporal scales. The following figures show the
463 temporal evolution of COVID-19 cases in Ourense's downtown, the third most populated city with
464 about 105,000 inhabitants (study area E in Figure 2.b). Figure 9.a represents the cases reported
465 on 15th April, while Figure 9.b is for 15th July. The first sub-figure represents a total of 254 points
466 and the second one 546 points, which is more than double. Even though it is a substantial
467 difference, it results difficult to identify incidence patterns. Figures 9.c and 9.d represent the same
468 data in a raster map where it is represented the cases density. These maps show a more clear
469 view of the infection risks in this area by considering the time evolution. It is also convenient to
470 use an aerial image as background, which allow us to clearly identify of the spatial patterns and
471 to propose hypothesis about the potential sources of infection.

(a)

(b)

(c)

(d)

Figure 9. Temporal evolution of COVID-19 cases within the city of Ourense. (a) Disaggregated mapping of cases (a) on 1st April and (b) on 15th July. Heat map based on cases density for the above dates: (c) 1st April and (d) 15th July. The areas with the highest concentration of dots correspond to the areas in red. Raster composed of 272 columns and 356 rows, with a cell size 10 x 10.

A more efficient strategy for decision-making is to reduce the mapping area to the intervention area, that is, the public space. Figure 10.a corresponds to a sample area located in the downtown of the same city. This area presents a medium-high urban density, with different types of city blocks and a limited presence of green spaces. The layout of the streets, although mostly rectilinear, is characterised by its lack of orthogonality. Figure 10.b shows the accumulated incidence of COVID-19 cases as of 15th July. Overlapping this figure, we locate and represent a series of socio-community centres and public facilities, such as educational centres, hospitals, pharmacies, and health centres. The simultaneous mapping of both factors allow us to evaluate the spatial correlation only considering the public space. Among other relevant aspects, we can identify some outbreaks near educational centres.

(a)

(b)

Figure 10. Analysis of the incidence of COVID-19 in a sample area of Ourense's downtown. (a) Aerial image of this sample area. (b) Mapping those areas with the highest concentration of cases within the public space, i.e. streets and parks. The rest of the urban space is represented with a grey dark colour. To add further value to these maps, we overlap a series of public facilities (such as educational centres, pharmacies, health centres) that potentially influence the spread of the virus. Raster composed of 272 columns and 356 rows, with a cell size 10 x 10.

6. Interpretation of the Results and Discussion

The COVID-19 pandemic has violently hit the world, generating a great uncertainty from the social, health, and economic perspectives. The situation of exceptionality and anguish

experienced with COVID-19 has forced the administrations and health authorities to propose unusual strategies in search of joining forces and finding answers. Some of them have understood the challenge and decided to share fine-grained and sensitive data with the scientific community. These data have made it possible to conduct complex analyses at all the spatial scales, allowing to achieve a better understanding of the spread of the virus.

Maps are fundamental tools that contribute to find solutions for emergencies such as those caused by COVID-19. Basically, geospatial analysis tools are capable to simplify complex, often abstract, realities turning them into graphical translations through arbitrary symbols. Given the emergence of COVID-19, geospatial analysis tools allow to simultaneously study all the environmental risk factors that may influence the virus spreading.

Spatial analysts must respond to what issue to represent, how and for what purpose. The first point determines the type and amount of information to be displayed. The second point determines aspects related to the symbology or the organisation of the information, among others. The last point determines the final objective of the map. Although there are a series of good practices in how a map should be configured, its result must be adapted to the final message it intends to convey and the audience to which it is transmitted [66]. The message must be clear, unambiguous, and self-explanatory. A clear representation of this message facilitates the subsequent steps related to the analysis and interpretation of the data.

During the pandemic, numerous institutions and governments have implemented web dashboards for visualizing COVID-19 data using GIS tools. Although most are informative to raise awareness, these sort of maps may be used as decision-making tools. However, it has some requirements related to updated, detailed and spatial disaggregated datasets, in addition to the need to implement appropriate mapping strategies for each particular objective. GIS tools allow to synthesize the complex abstraction of reality in data layers, which can be managed, organized, overlapped, and customized according to the requirements of the operator [67]. Beyond the value of these geospatial tools, the cartographic treatment of data by some of these web dashboards

has been widely criticised. In fact, it is frequent an excess of tools that take a long time to load and do not work correctly, the predominance of complex and counter-intuitive designs, and/or some platforms with limited effectiveness. The same happens with the design of the maps, with a tendency to over- or under- represent information, in addition to inappropriate uses of choropleth maps and different cartographic features such as datum, projection systems, and scales [68].

Here we present some mapping strategies using fine-grained and detailed COVID-19 data. For this purpose, we show different solutions in form of maps. Data are plotted using simple features (points, lines, and polygons), whose use depends on fundamental aspects such as the representation scale or the level of aggregation of the data. However, both aspects must be adjusted according to the privacy and sensitivity of the data. Health data mapping must pursue their objectives while preserving aspects such as the data integrity, user privacy, self-sovereign data ownership, as well as the compliance of the legislation on data protection. In consequence, it requires implementing strategies and approaches to data governance for ensuring that data are appropriately managed [69].

There is a complex trade-off between transparency to provide the more reliable information to society and to avoid the shortcomings derived from it. In the case of the pandemic, a very detailed representation of COVID-19 cases can be counterproductive creating an unjustified state of general alarm or leading to a rejection of certain individuals or communities. It is also applied to mapping strategies, being required to adopt certain arbitrary criteria (quantitative or visual) for preserving the anonymity of users. Just for example, an infected individual that is represented by a single dot may not be easily identified in an urban environment, but it can indeed be in a more rural environment. In the particular case of the region of Galicia, this is even more complicated in areas with an apparently urban physiognomy, such as in head towns, where data privacy cannot be guaranteed when finest grained data are represented. It requires the need to know the territory and to implement data aggregation strategies according with the particular characteristics of the study area.

Application of geospatial tools to the current pandemic is just one example more of the potential of GIS tools in health data management [70]. In the last few years, volume of health datasets has exponentially grown due to the enhanced capacity of portable devices like wearables, which have favoured the explosion of *personal health data* [71]. It explains the progressive shift of data and services to the cloud, partly due to convenience (availability of complete patient medical history in real-time) and cost savings [72]. This paradigm is favouring the creation of multidisciplinary work teams in order to reach more creative and efficient solutions to face a multifaceted issue such as the health management. Precisely in this respect that maps are an essential tool for integrating experts with different backgrounds in the same teamwork. An appropriate representation of data facilitates a comprehensive interpretation of the spatio-temporal behaviour of the virus from different analysis perspectives by increasing the interactions between experts. The importance of GIS tools goes far beyond traditional map generation. These may be used as centralized systems for managing data in (near)-real time. This represents a great benefit for subsequent steps of the pandemic such as the digital tracing for reported cases, but also for people at risk [70]. The success of interventions adopted by some countries is mostly based on this sort of technologies, which is greatly minimizing the impact of the virus on health, social, and economic terms.

Several aspects must be considered in our research. We use information from structured datasets, which have been pre-processed before to their representation. However, future in health management points more towards the representation unstructured datasets coming from personal devices, home sensors, and wearables. It will require to advance in new strategies and methodologies for handling, managing, and mapping these data. According to Fornace et al. [73], efforts will be focused on developing real-time high-resolution mapping strategies ready to be used with mobile technology-based applications.

Our proposal must be framed in a very exceptional context related with the COVID-19 crisis, which had encouraged many public administrations to share information. However, this experience must

go beyond. Nowadays, many governments are trying to implement open data platforms where data are available in non-proprietary formats, free of charges, and without distribution rights [74]. This, together with the ongoing digital transformation process in health management, requires the implementation of strategies that allow facing new challenges to improve population health, to enhance the quality of care services, and to reduce cost growths (i.e., the so-called *triple aim*) [75].

Finally, maps presented here serve to extract actual spatial patterns within a geographical context. In this way, we can evaluate the natural spreading of the virus in this region, but also the effectiveness of the interventions adopted to deal with it. A general reading of the figures show how this region was one of the least severely affected by COVID-19 in the first wave. This is largely due to the adoption of the harsh lockdown at a national level when the pandemic was still in an initial phase in this region. The spread of the virus presents a spatial pattern very similar to the regional structure of human settlements. Most of the reported cases were concentrated in the most populated areas, close to the *Atlantic Axis*. In future studies, the authors will conduct a more comprehensive analysis of these spatial patterns in this region at multiple scales.

Conclusions

Geospatial tools are playing a very relevant role throughout the current COVID-19 pandemic. Dashboards, web-based tools, and traditional maps allow sharing information with dwellers, whereas governments and authorities gain transparency for their public management. However, the importance of these tools must be further than merely informative, becoming an essential tool for decision-making in almost real time.

It requires a willingness to share fine-grained, detailed, and accurate information by responsible authorities. However, there are some concerns related to mapping these data to be considered. Among them, to keep the privacy of people or to avoid counterproductive effects such as

generating unjustified false alarms in the population. Geospatial data plays a key role in any visualization strategy. For this purpose, an appropriate and responsible management of geodata is required, adapting the maps to specific audiences and purposes. In addition to an optimal use of all the map's elements, the cartographer must implement the most appropriate strategies for mapping according to the particular objectives at any time.

In this article, we present some strategies for mapping fine-grained and detailed COVID-19 data. These data are geoprocessed with GIS tools and final maps are adapted to different objectives and scales. Our objective is to enhance the value of these data for making decision. Data visualization must be clear and adapted to the audience, by facilitating the integration of epidemiologists, health authorities, and policymakers to adopt the best decisions at multiple scales.

Availability of data and materials

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AUTHOR INFORMATION

Affiliations

1. Territorial Analysis research group, Galician Studies and Development Institute (IDEGA), University of Santiago de Compostela, Avda. das Ciencias 1, 15782, Santiago de Compostela, Spain

Ángel Miramontes and José Balsa-Barreiro.

**2. MIT Media Lab, Massachusetts Institute of Technology, 75 Amherst St., MA
02139, Cambridge, United States**

José Balsa-Barreiro.

Contributions

Hereby we confirm that all listed authors have contributed to the study. AM was mostly working on acquisition of data. JB was mostly focused on the analysis and interpretation of results. JB and AM drafted the article.

Authors' information

Prof. Dr. Angel Miramontes (<http://orcid.org/0000-0003-1162-3329>) is Professor at the Department of Geography and researcher at the Galician Studies and Development Institute (IDEGA), University of Santiago de Compostela, Spain. Correspondence to angel.miramontes@usc.es

Dr. José Balsa-Barreiro (<http://orcid.org/0000-0001-7348-4198>) is researcher at MIT Media Lab, Massachusetts Institute of Technology, MIT, Cambridge (MA), United States. He is also part of the Galician Studies and Development Institute (IDEGA), University of Santiago de Compostela, Spain.

Corresponding author

Correspondence to angel.miramontes@usc.es

826 **ETHICS DECLARATIONS**

827 **Ethics approval and consent to participate.**

828 Fine-grained data were yielded to the authors under confidentiality.

829 **Consent for publication**

830 Not applicable.

831 **Competing interests**

832 The authors declare that they have no competing interests. Not applicable.

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Figures

Figure 1

Number of reported cases and deaths from CoVID-19 in Spain since the beginning of the pandemic (31st January) until 15th November. Reported cases are shown in blue (Y-axis) and deaths in red (Y-axis inverted).

Figure 2

(a) The region of Galicia within Spain. The four background colours corresponds to provinces. The nodes in yellow, labelled with their respective names, represent the seven main cities. In this figure, it is also

represented the main road networks, i.e. motorways/highways (red lines) and railways (yellow lines). (b) The sample study areas analyzed in section 5 are located and bounded by the red boxes. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 3

Number of reported cases and deaths from CoVID-19 in Spain since the beginning of the pandemic (31st January) until 15th November. Reported cases are shown in blue (Y-axis) and deaths in red (Y-axis inverted).

(a)

(b)

Figure 4

Mapping COVID-19 cases officially reported in this region. (a) Representation of the most fine-grained level of detail. In this map, each single red dot corresponds to a reported case, which is spatially located based on the private address. (b) Mapping using a heat map, where areas with the highest point densities corresponds to the areas in red. Raster composed of 358 columns and 323 rows, with a cell size 1000 x 1000. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 5

Mapping COVID-19 cases officially reported at a local scale of aggregation (municipalities). (a) Number of cases per 100,000 inhabitants. (b) Number of cases per 100 km². In both cases, the intervals are distributed in regular quartiles. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 6

Number of CoVID-19 cases officially reported at a local scale of aggregation (municipalities). (a) Mapping data for the whole region. (b) Mapping data for a small case study located in the region of Vigo. Value intervals are distributed in regular quartiles. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

(a)

(b)

(c)

Figure 7

(a) Number of COVID-19 cases officially reported at an intermediate scale of aggregation (census districts) in the municipality of Vigo. Value intervals are distributed in regular quartiles. (b) Zooming into a specific area in the downtown of Vigo. (c) Disaggregated representation of reported cases in the same area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any

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(a)

(b)

Figure 8

Number of COVID-19 cases officially reported in a specific area of A Coruña. (a) In yellow, we represent the location of this sample area within the city. (b) Data mapping of reported cases at the lowest scale of aggregation (street sections). Note: The designations employed and the presentation of the material on

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Figure 9

Location of COVID-19 cases in different sample areas: (a) A specific area in the downtown of the city of Santiago de Compostela, (b) the centre of a head town located in the northwestern part of the region, and (c) a small village of undetermined location by privacy concerns. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its

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Figure 10

Temporal evolution of COVID-19 cases within the city of Ourense. (a) Disaggregated mapping of cases (a) on 1st April and (b) on 15th July. Heat map based on cases density for the above dates: (c) 1st April and (d) 15th July. The areas with the highest concentration of dots correspond to the areas in red. Raster composed of 272 columns and 356 rows, with a cell size 10 x 10. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on

the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

(a)

(b)

Figure 11

Analysis of the incidence of COVID-19 in a sample area of Ourense's downtown. (a) Aerial image of this sample area. (b) Mapping those areas with the highest concentration of cases within the public space, i.e.

streets and parks. The rest of the urban space is represented with a grey dark colour. To add further value to these maps, we overlap a series of public facilities (such as educational centres, pharmacies, health centres) that potentially influence the spread of the virus. Raster composed of 272 columns and 356 rows, with a cell size 10 x 10. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.