ARTICLE

Mapping COVID-19 in Context: Promoting a Proportionate Perspective on the Pandemic

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Introduction

A novel coronavirus was discovered in Wuhan, China, in late December 2019. Later labelled SARS-CoV-2, this second severe acute respiratory syndrome (SARS) coronavirus (CoV) causes COVID-19, a respiratory disease with symptoms similar to those of influenza. The process for polymerase chain reaction (PCR) testing to detect genetic SARS-CoV-2 fragments in humans was developed by Corman and others (2020) at the Charité Hospital in Berlin, Germany, and quickly adopted by the World Health Organization (WHO) as the reference lab test for COVID-19. The virus was discovered in countries around the globe during January and February 2020, and the WHO declared the COVID-19 pandemic in early March (Cucinotta and Vanelli 2020). The WHO's definition of a pandemic requires that a novel respiratory virus, to which humans have little or no immunity, spread aggressively in multiple regions of the world. There has been much debate about the motives of the WHO for removing a reference to a virus's morbidity and mortality ("enormous numbers of deaths and illness") from its Web site just...
before the declaration of the 2009 swine flu as a pandemic (Doshi 2011).

In mid-March 2020, researchers from Imperial College, London, UK infamously predicted millions of deaths worldwide (Walker and others 2020) using a computer model that spawned extensive mitigation and suppression strategies (“lockdowns”) across much of the globe. Others warned of critical supply shortages (Ranney, Griffeth, and Jha 2020) in a “once-in-a-century pandemic” (Gates 2020) that would only end when “cases … go to zero” (Roser and others 2020). In contrast to the widespread alarmism, some distinguished epidemiologists, statisticians, and other researchers took a more measured stance. For example, Ioannidis (2020a) found that numerous medical papers with exaggerated estimates of key metrics for COVID-19 were withdrawn before or after peer review; Bendavid and Bhattacharya (2020) opined that the COVID-19 fatality rate was overestimated by several orders of magnitude; Jewell, Lewnard, and Jewell (2020) cautioned against trusting model-based epidemic projections for policy making; and Lourenço and others (2020) predicted that future epidemic “waves” of COVID-19 would be less deadly than the first wave due to cross-immunity from seasonal coronaviruses causing the common cold. Pre-existing immunity in the population through memory T cells was reviewed by Doshi (2020) and pegged at 20% to 50% of people. This and the variability in individual susceptibility to infection led Gomes and others (2020) to estimate the herd immunity threshold for COVID-19 at only 10% to 20% of a population.

In a detailed study of one of Germany’s first infection hot spots, Streeck and others (2020) found that 15.5% of the population of Heinsberg county had been infected and likely acquired immunity, representing five times the known SARS-CoV-2 infections in this region. Similarly, Havers and others (2020) estimated between 6 and 24 times as many infections as in the official COVID-19 case count, and concluded that for most of their 10 US sites, the multiplier was at least 10. Back in Heinsberg, Germany, Streeck and others (2020) also determined that participation in large carnival gatherings in mid-February had increased the likelihood of being infected, but that the secondary infection risk at home was limited to less than 50% and inversely related to household size. The infection-fatality rate (IFR) in the Heinsberg study amounted to 0.36%, about a factor of 10 lower than the WHO’s initial estimate of a case-fatality rate (CFR) of 3% to 4%. The CFR was used prior to the realization that a significant proportion of SARS-CoV-2 “infections” remain asymptomatic and therefore undetected, resulting in an IFR that is much lower than the CFR. A working paper by Oke and Heneghan (2020) estimates an IFR in the range of 0.1% to 0.35%, while a meta-analysis of 36 sero-prevalence studies by Ioannidis (2020b) infers an IFR of 0.27%. Ioannidis (2020c) was heavily criticized for his early, optimistic estimates, but he was recently vindicated when his updated analysis based on 61 studies confirmed a median IFR of 0.27% and was published in the WHO Bulletin.

While suggesting social media monitoring in support of the COVID-19 pandemic response, Depoux and others (2020) also caution that social media allowed the confusion and panic to spread faster and farther than the pandemic itself. Among other dissenting views, Atlas (2020) presented five key facts against the continuation of the initial lockdowns, while Kuhbandner and Homburg (2020) demonstrate that the late-March lockdown in the UK came too late to have had an effect on the epidemic curve. Books titled “Corona False Alarm?” by Reiß and Bhakdi (2020) and “Unreported Truths about COVID-19 and Lockdowns” by Berenson (2020) summarize similar concerns about the pandemic and the global public health response measures. Among the exceedingly rare dissenting viewpoints from within geography are Hulmé’s (2020) argument against a singular focus on COVID-19 and the use of one-dimensional models for long-term societal decision-making and Dorling’s (2020) short piece asking the question “Is the cure worse than the disease?” Dorling points to the collateral damage generated by sweeping restrictions on economic, health, and social systems, including future excess deaths and years of life lost due to unaddressed heart attacks and strokes, cancelled or delayed cancer treatment and prevention, starvation, and mental illness (for more details on the collateral damage of lockdowns, see, e.g., Ioannidis 2020d, Schippers 2020).

What are the consequences of this controversial environment for mapping the pandemic? COVID-19 maps, like the ubiquitous epidemic curves, are prone to amplifying messages about the spread of the virus and the disease, regardless of the data issues discussed above. Early on, GIS researchers such as Kamel Boulos and Geraghty (2020) celebrated the potential of geospatial mapping, tracking, and artificial intelligence to combat the COVID-19 pandemic. More recently, voices of caution were raised with respect to the misuse of Web maps and their contribution to an “infodemic” (Mooney and Juhász 2020), along with significant gaps and inconsistencies in the underlying health data (Rosenkrantz and others 2021). Mooney and Juhász (2020) presented a comprehensive list of 10 types of cartographic issues found in COVID-19 Web maps, including those related to scale, spatial units, incorrectly used map types, crowding of map symbols, data classification, lack of data normalization, and omission of information on data uncertainty.

In the magazine Canadian Geographic, Brackley (2020c) illustrates the use of dasymetric mapping to overcome the issue that choropleth maps portray COVID-19 equally across populated and unpopulated parts of the underlying spatial units. In a follow-up post, Brackley (2020a) demonstrates the process of mapping infections in relation to total population and presents a cartogram with Ontario health
units scaled in proportion to infection rates. In a third post, Brackley (2020b) addresses the map reader’s emotional reaction to different map styles. He presents examples of published COVID-19 maps where intense, dark map colours and large and dense symbols generate overly negative associations, and contrasts these with examples of lighter maps that are in better proportion to the underlying values and spatial patterns. In the blogosphere, Field (2020) and Rinner (2020) also discuss basic cartographic missteps in coronavirus maps produced by government and news media, including the misuse of alarming red colour schemes. Finally, the story map “COVID-19 Context,” in which North (2020) normalizes raw-count data by Toronto neighbourhood population, separates community cases from those that occurred in long-term care homes, and suggests socio-economic variables to analyse alongside COVID-19, was another inspiration for writing this article. Notwithstanding tragic individual illness and deaths caused by SARS-CoV-2, as well as localized challenges to health care systems, it is becoming clear that COVID-19 is not presenting an eminent threat to global public health. Maps are a key tool for understanding the status and progression of the pandemic. Particular attention should therefore be given to providing a proportionate perspective. The following sections illustrate the mapping of problematic and more useful metrics at three jurisdictional scales and discuss the possible uses and misuses of the resulting maps.

Data and Methods

The spread of COVID-19 has been described by a confusing array of metrics, including the following:

- estimated number of infections
- detected infections (“cases”)
- incidence of cases per 100,000 population
- PCR test positivity rate
- number and rate of hospitalizations
- number and rate of intensive-care unit (ICU) patients
- number and rate of patients on respirators
- number of fatalities, fatality rate per million population
- CFR
- IFR

Most of these metrics exhibit significant conceptual and practical accuracy issues. The true number of infections in the population is unknown and can only be estimated from case and death counts, or from antibody testing. The number of cases is entirely dependent on the PCR test, which has several critical flaws (e.g., Tang and others 2020): (1) it is dependent on the total number of tests conducted, which has increased dramatically in most countries since the beginning of the pandemic; (2) it is dependent on the a priori probability based on sampling strategy (e.g., testing of symptomatic or asymptomatic people); (3) like every lab test, it produces erroneous results, where the false positives are particularly problematic during phases of low prevalence; and (4) conclusions drawn from the test results depend greatly on the procedure, in that the unregulated cycle threshold (Ct value) can produce a “functional false-positive PCR test” that does not indicate infectiousness (Rational Ground 2020, time stamp 51:10).

The test positivity variable is used to overcome the dependency on total tests completed, but it still suffers from the other three limitations of the PCR test. The COVID-19 hospitalization, ICU, and death variables also depend on the PCR test results; in addition to the issues with the test itself, the way in which its results are applied to hospitalization and death counts in many countries is also questionable. Since hospitals conduct SARS-CoV-2 tests upon entry, patients entering hospital for any other reason will be labelled as COVID-19 patients if their tests are positive. Similarly, the death of an individual who had tested positive for SARS-CoV-2, often weeks before death, will be added to the COVID-19 tally irrespective of the primary cause of death (e.g., Heneghan and Oke 2020). Additional metrics for monitoring the spread of SARS-CoV-2, such as the case doubling period in days and the effective reproduction number (the average number of infections caused by each case), depend on the flawed case counts as well.

The geospatial and attribute data used in the maps created for this research were obtained from a variety of sources. For the map of the city of Toronto, COVID-19 data were downloaded from Toronto Public Health’s COVID-19 dashboard (City of Toronto 2020b), while neighbourhood boundaries were retrieved from the city’s open data catalogue (City of Toronto 2020a).

For the maps of Canada by provinces, COVID-19 data were downloaded from Esri Canada’s dashboard (Esri Canada 2020b), while hospitalization data were obtained from the Canadian Institute for Health Information (2020) and boundary files and mortality statistics came from Statistics Canada (2016; 2020b).

For the world map, COVID-19 data were retrieved from Our World in Data (Roser and others 2020) with country boundaries (administrative level 0) obtained from the Natural Earth repository (Natural Earth 2020).

Mapping COVID in Toronto

The Web page “COVID-19: Status of Cases in Toronto” (City of Toronto 2020b) includes a Tableau data visualization app with an interactive map of neighbourhood statistics. The default view opens with a choropleth map of total cases detected from 21 January to 22 October 2020 (see Figure 1a); this mapping technique should never be used to map raw-count data (e.g., Field 2020; Rinner 2020).
To the credit of Toronto Public Health, they modified the app after North (2020) wrote his critique on 16 June 2020. They included the option to change the variable shown from case counts to cases per 100,000 residents. In addition, the user can now separately map cases arising sporadically in the community from outbreaks in institutions such as long-term care homes. Finally, it is also possible to change the display from cumulative cases/rates to only recent cases from the last 3 weeks.

Figure 1b suggests that the rate of recent community cases has a somewhat different distribution from that of the cumulative all-case counts. The cartographic symbology

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**Figure 1.** Screenshot of Toronto neighbourhood map of (a) COVID-19 cases (map is not consistent with basic cartographic principles); (b) recent, sporadic cases per 100,000 people

Sources: City of Toronto (2020b) as of 22 October 2020. Contains information licensed under the Open Government Licence – Toronto. Map data © Mapbox, © OpenStreetMap contributors.
seems to be based on an unclassed colour scheme that is susceptible to the impact of outliers. Nevertheless, the variable shown – rate of recent cases in the community – is most likely of interest to residents who want to examine the current prevalence of COVID-19 in their neighbourhoods. It is unfortunate that this variant of the map requires the user to make three changes to the default view.

The values shown in Figure 1b range up to about 400 recent community cases in 100,000, or 0.4% of the residential population. Representing such a small proportion (see pie chart in Figure 2a) with a dark colour is questionable, although Toronto Public Health did avoid the "emotional" colour red (Mooney and Juhász 2020). To put the rate into visual proportion, a dot density map is proposed instead (Figure 2b). In that map, a grey dot represents 25 neighbourhood residents, while a striking black dot, plotted on top of the population layer, represents 25 recent, sporadic cases. The unit value of 25 was determined by trial and error in conjunction with the dot size (0.5 point), so that the map layer containing the larger values (residents) would present a spatial pattern that was "neither too accurate nor too general" (Dent 1999, 166). Importantly, the unit value for the other layer (cases) had to be set to the same value to maintain comparability between the layers. Therefore, rounding of small numbers of cases per neighbourhood to the nearest multiple of 25 also had to be taken into account. As a result, 37 neighbourhoods with 1–12 cases fell below the symbol threshold for the case variable.

If you are trying to find COVID-19 cases in this map and feel as if you are playing a Where’s Waldo? children’s game, that is perhaps indicative of the low likelihood of coming across an infected individual when moving around town. In addition, we have to assume that most detected cases abide by the self-isolation requirements and therefore do not pose a risk of infection to other community members. That risk may be more related to the prevalence of undetected, often asymptomatic carriers of the virus – information that is not available and thus not shown on these maps, despite their implicit purpose of representing local infection risk.

Mapping COVID across Canada

In terms of published Canada-wide COVID-19 maps, most media continue to offer the misleading and cartographically incorrect types of products criticized by Brackley (2020b), Field (2020), Mooney and Juhász (2020), and Rinner (2020). Sadly, the Canadian Broadcasting Corporation (CBC) provides one of the worst examples (Figure 3), which uses an ominous red colour scheme on an incongruous choropleth map of raw counts of confirmed COVID-19 cases by province or territory. The Toronto Star’s map of North American coronavirus deaths by province/territory or state employs a more subtle teal colour scheme and suitably projects the map (Toronto Star 2020). However, it still suffers from improper symbology for raw totals and an issue with the classification scheme, since the highest class (> 50,000 deaths) is not present on the map, leaving coarse value ranges and too little colour variation for the remaining classes.

In contrast, Esri Canada uses proportional circles to represent the 7-day new case rates per 100,000 people on top of

Figure 2. (a) Proportion of recent (active) COVID-19 cases in the community; (b) Where’s Waldo-style dot density map of recent community cases and total neighbourhood populations.

Data sources: City of Toronto (2020a, 2020b) as of 22 October 2020. Contains information licensed under the Open Government Licence – Toronto.
a choropleth map of the number of days since the last new case was reported (see Figure 4). The luminance-focused proportional symbols still look quite alarming and the site suffers from the apparent inability of Esri’s online products to apply non-Mercator projections. To their credit, Esri Canada’s site was one of the first that included active and recovered COVID-19 cases rather than exclusively displaying cumulative cases and deaths. In addition to these positive outcomes, they also provide graphs since early in the pandemic for the policy-relevant metrics of hospitalizations and ICU occupancy and offer their curated dataset for free download.

Arguably, the tangible health outcomes represented by hospitalizations and deaths are more informative than case counts for situation awareness and decision-making. For example, to understand hospital use and remaining capacity, we can map hospital beds occupied by SARS-CoV-2-positive patients. At a national scale, as of 22 October,
around 2% of “other” (non-specialized) acute-care beds were used for COVID-19 patients (Figure 5a). To accurately represent this policy-relevant information, Figure 5b proposes an unclassified choropleth colour scheme with grey proportionate values. Of course, the low numbers (a good thing!) result in a rather bland, but suitably comforting map.

Updated demographic data indicate that Canadians mourned 287,465 all-cause deaths from July 2018 through June 2019 (Statistics Canada 2020c), an average of close to 800 deaths per day. The primary causes of deaths in 2018 were cancers and cardiovascular diseases, followed by strokes, accidents, and chronic lower respiratory disease (Statistics Canada 2020a). According to the same source, influenza and pneumonia accounted for the sixth most deaths in 2018 and cost a total of between 6000 and 9000 lives each year between 2014 and 2018, or on the order of 2% to 3% of all deaths. Putting COVID-19 deaths into perspective with total mortality for the first eight months of 2020, we can see that the SARS-CoV-2 “killer virus” accounted for less than 5% of all deaths (Figure 6a). As above, the cartographic symbol in Figure 6b reflects the percentage values by province, with Quebec standing out with 12%, Ontario with 4%, and all other provinces with minimal values. In addition to these striking geographic disparities, we can deduce that COVID-19 has been a significant, but far from overwhelming, source of deaths in Canada.

Mapping COVID around the World

At the time of writing (October 2020), COVID-19 has been associated with over one million deaths and 45 million confirmed cases worldwide since the discovery of SARS-CoV-2. With 7.8 billion people inhabiting the planet, there is about one infection for every 175 humans. Mapping cumulative cases as of a specific date (e.g., 22 October 2020; see Figure 7) is in itself misleading, as the map suggests a snapshot rather than a summary of events over an extended time period. The map shown from OurWorldInData.org is misusing the choropleth symbology to portray raw count data, as seen above. In addition, the striking red colour scheme and the non-linear classification scheme with medium colours representing as little as one thousandth of the largest values distort the display towards an unsettling experience.
Brazil, and a few other South American countries seem to have reached or exceeded the upper limit of herd immunity based on hidden cases, which suggests that their hidden cases are overestimated, the herd immunity threshold is higher than 20% of the population, or other local factors are at play. Several other European and South American countries, along with India, Russia, and South Africa, seem to be approaching the lower limit of herd immunity based on hidden cases. Overall, the map aims to provide a reassuring view of the global status of the pandemic. Countries with the largest numbers of detected infections can hope to be on their way to immunity, while those with comparatively few cases are currently less severely affected by the pandemic, although they may be facing rising metrics for a period of time in the near future.

One purpose of mapping cumulative case counts could be to determine whether countries may be approaching natural herd immunity to SARS-CoV-2. The sample map in Figure 8 uses proportional diagrams to present COVID-19 cases as a percentage of total population as well as in relation to the 10% to 20% estimated herd immunity range (Gomes and others 2020) shown through the outer ring of each diagram (light grey segment). In the diagram's core, we see confirmed COVID-19 cases from PCR testing (black segment) along with an estimate of undetected ("hidden") infections (grey segment) at 10 times the number of known cases (following the estimate by Havers and others 2020).

At the given cartographic and visual scale, hardly any country has noticeable case counts, with the exception of Brazil and the United States. The United States, Spain, Brazil, and a few other South American countries seem to have reached or exceeded the upper limit of herd immunity based on hidden cases, which suggests that their hidden cases are overestimated, the herd immunity threshold is higher than 20% of the population, or other local factors are at play. Several other European and South American countries, along with India, Russia, and South Africa, seem to be approaching the lower limit of herd immunity based on hidden cases. Overall, the map aims to provide a reassuring view of the global status of the pandemic. Countries with the largest numbers of detected infections can hope to be on their way to immunity, while those with comparatively few cases are currently less severely affected by the pandemic, although they may be facing rising metrics for a period of time in the near future.
Geospatial analysis and visualization have tremendous potential to respond to and manage infectious disease threats, and an incredible number of global, regional, and local maps and spatially enabled dashboards for COVID-19 have been published. Yet many of these maps and dashboards present serious cartographic problems, including improper map projection, raw count choropleth maps, alarmist colour choices, and illogical classification schemes. These issues exacerbate concerns with the reliability and representativeness of the underlying data, and could thereby contribute to misleading public opinion and ensuing policy decisions.

One of the challenges of mapping the pandemic may be linked to the unclear purpose of many published maps. Geographically visualizing raw data is a suitable approach to exploratory analysis (e.g., Gatrell and Bailey 1996), in particular in a context of uncertainty such as this pandemic, yet the visualization should support interactive “playing” with the representation. While Toronto Public Health’s neighbourhood map (Figure 1) allows users to switch between case counts and case rates, it does not support changes to the data classification and associated colour scheme, and most other examples (Figures 3, 4, and 7) are even more static with respect to these critical cartographic choices. Additionally, geovisualization is typically seen as a “private” activity conducted by expert analysts, not members of the general public (Andrienko and Andrienko 1999; Kraak 1998; MacEachren 1994); it will be interesting to analyse the role that maps may have played in the politics of, and public health responses to, COVID-19 around the globe.

The proposed alternative maps in this article (Figures 2, 5, 6, and 8) were created to contrast with the “mainstream” view of the pandemic. They are meant to illustrate the range of possible visualizations of the same or related public health data. Due to their printed or static electronic form, they are not interactive either, and thus not suitable for data exploration. Therefore, they may also illustrate the difference between interactive, and potentially harmful, mapping tools for data exploration, on one hand, and constrained, yet inflexible, maps to answer specific questions, on the other hand. For example, mapping COVID-19 cases could serve to answer two very different questions: (1) what is the current risk of infection from participating...
wrote a statement in her support (URISA 2020), noting that the GIS Code of Ethics requires GIS professionals to complete their work with integrity, even when put under external pressures. While in this case influence may have been exerted to paint the pandemic in a more positive light, cartographers and GIS analysts would hopefully also push back if they were subjected to demands to participate in undue fear-mongering with maps. Ultimately, the pandemic reinforces the need to respect and promote the principles of cartography and GIScience emphasized by Brackley (2020a, 2020b, 2020c), Mooney and Juhász (2020), and Rosenkrantz and others (2021), including those concerning data accuracy, the proportionality of data, and their meaningful visualization.

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