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The conspiracy of Covid-19 and 5G: Spatial analysis fallacies in the age of data democratization

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ABSTRACT

In a context of mistrust in public health institutions and practices, anti-COVID/vaccination protests and the storming of Congress have illustrated that conspiracy theories are real and immanent threat to health and wellbeing, democracy, and public understanding of science. One manifestation of this is the suggested correlation of COVID-19 with 5G mobile technology. Throughout 2020, this alleged correlation was promoted and distributed widely on social media, often in the form of maps overlaying the distribution of COVID-19 cases with the instillation of 5G towers. These conspiracy theories are not fringe phenomena, and they form part of a growing repertoire for conspiracist activist groups with capacities for organised violence. In this paper, we outline how spatial data have been co-opted, and spatial correlations asserted by conspiracy theorists. We consider the basis of their claims of causal association with reference to three key areas of geographical explanation: (1) how social properties are constituted and how they exert complex causal forces, (2) the pitfalls of correlation with spatial and ecological data, and (3) the challenges of specifying and interpreting causal effects with spatial data. For each, we consider the unique theoretical and technical challenges involved in specifying meaningful correlation, and how their discarding facilitates conspiracist attribution. In doing so, we offer a basis both to interrogate conspiracists' uses and interpretation of data from elementary principles and offer some cautionary notes on the potential for their future misuse in an age of data democratization. Finally, this paper contributes to work on the basis of conspiracy theories in general, by asserting how – absent an appreciation of these key methodological principles – spatial health data may be especially prone to co-option by conspiracist groups.

1. Introduction

When COVID-19 reached European and American cities, alternative knowledge claims quickly emerged confronting official accounts of the cause of the virus. Rather than spawning new conspiracy theories, COVID-19 has led to improvisations on many older ones, in this case linking it to mobile electromagnetic frequencies, using many of the same logical and methodological fallacies to "prove" their veracity (Sturm and Albrecht, 2021). For example, the 2020 Christmas morning suicide bomber of the Nashville AT&T building was possibly motivated by 5G "radiophobia" conspiracy theories, but not necessarily their correlation to COVID-19 (Burgess, 2003; Luscombe, 2020). Improvising from these established conspiracy theories, tens of thousands contributed to the "trending" of @5Gcoronavirus, or have observed that within cities, the spatial distribution of the density of COVID-19 infection correlates with the density of 5G towers, suggesting there is a causal relationship between them (Ahmed et al., 2020; Jolley and Paterson, 2020). This theory was promoted by Manchester Councillor Kenneth Dobson, who shared spatial distribution maps correlating cases of COVID-19 with 5G infrastructure (Griffiths, 2020, see Appendix 1, item 4). Other celebrities have also made the connection, including Sky News presenter Eamonn Holmes, boxer Amir Khan, actors John Cusack and Woody Harrelson, and singer MIA (Andrews, 2020). This theory has motivated the burning of at least 77 mobile towers in the UK alone (Chan et al., 2020). Michael Gove, UK Cabinet Secretary, said in an April 2020 press conference that the correlation was "dangerous nonsense" and asked Professor Steve Powis, National Medical Director of NHS England, to confirm with his scientific assessment: "I'm absolutely outraged, absolutely disgusted,

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that people would be taking action against the very infrastructure that we need to respond to this health emergency" (Parveen and Waterson, 2020). The UK government even went so far as to post a fact sheet on their gov. uk site to dispel the theory, and Facebook has been removing 5G-COVID posts citing that the theory could cause "physical harm" (Griffin, 2020).

Conspiracy theories in general carry potentially serious public health risks, especially as anti-vaccination beliefs are already found to be associated with conspiratorial thinking (Goldberg and Richey, 2020, p. 107). The perceived risks surrounding 5G were buoyed initially by real US-Chinese geopolitical tensions, centred on the perceived security risks of Huawei devices and communications technologies. The arrest of Huawei's Chief Financial Officer in 2018, and the subsequent banning of Huawei from conducting business with US-based entities, gave fuel to conspiracy theories of Chinese technology in particular, but also surrounding 5G in general. Organised opposition to 5G rollout has been especially visible in the UK, where interest groups and individuals have in places succeeded in pushing back against 5G rollout (Cellan-Jones, 2020). Adherents of conspiracy theories have surmised that 5G weakens the immune system, infects people directly with COVID-19, or causes symptoms that simulate viral infection. Others have argued that 5G was first tested in Wuhan, China, the city linked to the first cases of COVID-19, which proves it is the cause of the virus. Still others claim that COVID-19 is only the latest iteration of mobile towers causing disease; before this, 3G caused SARS, and 4G Swine flu (Reuters, 2020). In all iterations, 5G is depicted as either "Satan's strategy" to advance the apocalypse, or the work of a techno-capitalist government cabal that seeks to reduce the population, profit from a vaccine, or embed micro-chips into the vaccine for the purposes of surveillance or control (Wu, 2020).

But these beliefs may have serious public health consequences. In the UK, a survey found that 21% of people agree that 5G causes COVID-19 (Freeman, 2020, p. 6, though Sutton and Douglas (2020) argue 21% may be greatly exaggerated by virtual of study design). An Oxford Survey found that 40% of respondents believed "to some extent the spread of the virus is a deliberate attempt by powerful people to gain control" (OCEANS, 2020) and only 64% are sure they will take the vaccine (Sherman et al., 2020). An American study, by contrast, found that only 11% of respondents agreed 5G and COVID were correlated (Enders et al., 2021, p. np). The 5G-COVID-19 conspiracy theory arrives in a context of growing scepticism over public health institutions and measures. With trust in pharmaceutical companies and government agencies already a profound predictor of vaccine confidence (Jamison et al., 2019), the potential for conspiracy theory narratives to attribute further outcomes to sinister motivations (i.e. as with autism and the MMR vaccine) is concerning. The ways that COVID-19 conspiracy theories draw on mistrust in government also holds the potential to solidify existing levels of distrust, especially where political party disaffiliation is found to be negatively associated with vaccine completion (Buckman et al., 2020). With education and trust shown to be predictors of both conspiracy theory beliefs and public health compliance/confidence, it is ever more essential that the evidence base of such narratives is interrogated (Tomeny et al., 2017; van Prooijen, 2016).

Postings asserting the correlation between COVID-19 cases and 5G share some common features (see Appendix 1). They typically contain point data in the form of 5G-carrier tower locations, some with added coverage radii, and choropleth data on COVID-19 (mainly confirmed case and death counts, or case and death rates). The correlation is typically depicted using overlays of point distribution and regional rate data, with COVID data aggregation varying from national (country) to sub-national (i.e. U.S. States). There is little discussion of aggregation issues, or of the comparability between point data (that identify items in location or specific places) and ecological data (that identify some characteristic of a larger area such as a county, local authority area, or electoral division). They typically do not offer measures of correlation effect size (in instances where such may be possible), and communication is thus primarily visual. For students and practitioners, the correlation between 5G and COVID-19 is an archetypal example of several methodological problems in spatial analysis. But there is a more urgent sense in which this issue needs discussing. We live in space-time of unprecedented data production, with all its attendant opportunities and risks in public health and medicine. Positively, the greater velocity and resolution of spatially-attributed data can enhance the complexity of models fitted, and theories tested by human geographers (Kitchin, 2013, p. 263). Negatively, they signal the greater potential to detect spurious correlations merely as a result of the size of the dataset, and causal pathways are more challenging to determine amidst greater noise accumulation (Calude and Longo, 2017; Fan et al., 2014).

Indeed, as we discuss below, some commonly ignored and misunderstood risks inherent to spatial data such as serial correlation render careful interpretation of effects more challenging still. At its worst, the greater availability and dimensionality of data suggest an 'end of theory', where correlations in data of high volume and dimensionality are seen as self-evident, or where the greater likelihood of bias and error is unacknowledged (Brunsdon and Comber, 2020, p. 92; Kitchin, 2013, p. 265; Kitchin and McArdle, 2016, p. 3). Whilst the data commonly cited by conspiracists (we use this term to denote adherents of this conspiracy theory) in the case of 5G-COVID are of lower resolution and complexity than that of 'big' data, however defined, the selective co-option and poor modelling of increasingly public data by conspiracists is of growing concern. As conspiracy theorists often presume that momentous events must be of sinister origin (Leman and Cinnirella, 2007), and as such disparate groups congeal around broad alliances between the far-right, leftward, and esoteric grouping, it is important that we consider the role played by selective computational data methods – and its interpretation – in fueling further conspiracy theory propagation (Sturm and Albrecht, 2021). There is already a noted spatial character to anti-vaccination beliefs, which cluster in both time (immediately following vaccine-related news coverage), and space (those of large populations, and high income – Tomeny et al., 2017, p. 171). 5G conspiracism is a distinctly urban concern. As a predominantly urban technology, it is currently installed in areas of high population and production densities, and higher affluence (Jones and Comfort, 2020). As one of the central promises of smart city implementation, 5G has also become an indicator of the rural/urban technological divide (Rao and Prasad, 2018). The class and geographical bias of 5G is also reflected in the pattern of responses to COVID-19, as lockdowns were initially implemented most quickly in wealthy urban areas.

Taken together, the conspiracy theories that correlate 5G and COVID-19 found their initial favour on alt-right internet media sites, and their associated protest movements have been most active in sites of perceived power (cities and government buildings in the U.S. and U.K.) (Sturm and Albrecht, 2021). Combined with social media (Wang et al., 2019), this is a potent mix for the spread of misinformation based on poor urban data science, and 5G-COVID conspiracy theory poses a direct risk to public wellbeing by distracting from legitimate mitigation strategies. In the following sections, we argue that the combination of conspiracy thinking, coupled with several inherent issues in geographical data analysis, signal a potentially dangerous condition where future conspiracy theorising within the collective imagining and misuse of data science could cause damage to health policies and city practices absent the analytical principles we later discuss (McMillan et al., 2016, p. 2936). We do this in two stages. We begin with an overview of some common concepts and features of conspiracism and conspiracy theories, showing its basis incorporation of common fallacies of reasoning, and its modes of contestation of power and authority. Our substantive discussion focuses on its treatment of data, and the specific risks associated with misinterpretation of spatial data. We discuss the specifics of this under three headings: the unique nature of *emergent properties* as a phenomenon of social processes, the risks associated with establishing *ecological correlation*, and how *autocorrelation and spuriousness* pose specific risks general to social science data, but of a particular variety with geographical data. In so doing, we offer a basis for medical and spatial analysis practitioners, public, and media to interrogate the foundations of the alleged correlation between 5G infrastructure and COVID-19 cases – and doubtless future assertions in other domains. In light of the unique challenges posed by geographical data analysis, coupled with the cognitive frames of conspiracist reasoning, we suggest in the final section that these phenomena heighten the likelihood that patterns and conjunctions such as 5G-COVID-19 will be inferred as causally significant, despite an absence of sound evidence.

2. Conspiracy theories and statistical fallacies

Past studies of determinants and covariates of belief in conspiracy theories show strong associations with political powerlessness and education. Experimental studies suggest the tendency to perceive patterns in data is more likely amongst those with perceived lack of control (Whitson and Galinsky, 2008), whilst observational data show that belief in government conspiracy theories is more likely amongst structurally disempowered groups (Thompson et al., 2021). Endorsement of conspiracy theories is negatively correlated with education, with feelings of powerlessness and subjective social class forming key aspects of the causal mechanism (van Prooijen, 2016). Thus, existing literature reveals a mix of cognitive, dispositional, and contextual factors in the endorsement of conspiracy theories, and tendency to perceive patterns of causality in seemingly-unrelated events. Van der Wal et al. (2018, p. 972) show how conspiratorial explanations were more likely for events that were seemingly socially significant. This is important, as the tendency appears more pronounced in non-random phenomena (to which may also include COVID-19 and 5G), where the question is not 'whether' something caused the outcome, but 'what'. Whilst these studies provide valuable insight into the potential mix of factors influencing conspiratorial bias, there is an urgent need to interrogate the theories themselves in their socio-medical and socio-political context. With growing evidence of the embeddedness of conspiracy theory discourse in political contexts of powerless and polarisation, the need is more urgent still.

The wider literature suggests that 5G-COVID conspiracy theorists rely on some commonly recognisable fallacies identified within philosophy and psychology: errant data, patternicity, and conjunction fallacies. Conspiracy theory ideation often avails of what Keely (1999, p. 118) calls "errant data", that is, unaccounted for or unexplained data that is not present in received accounts in the official media. The veracity of the theory is measured by the unified explanation of both common and errant data; therefore, conspiracy theories often claim to explain more than the competing accounts. The problem for conspiracy theorists is that no theory can explain all data, and moreover, not all data is 'true'. Errant data are part of a larger psychological necessity of pattern perception, and the disposition to find patterns in from otherwise disparate events has been called "patternicity" (Shermer, 2008). This false positive error, combined with confirmation bias and hindsight bias, allow for conspiracy theorists to assert an existing pattern - in this case, mobile electromagnetic frequencies - and reassign its sinister effect from surveillance to the spread of COVID-19. However, Enders et al. (2021) found that the impact of social media on such is a form of biased assimilation. Conjunction fallacies are errors of probabilistic reasoning where people overdetermine the prospect of co-occurring phenomenon (Enders and Smallpage, 2019). Conspiracy theorists tend to view conjunctive phenomena as having a secret or underlying causal relationship "subjectively representative of events in general and thus more subjectively probable than alternative explanations" (Brotherton and French, 2014, p. 240). Such conspiracy theory ideation is therefore productive of cognitive correlates. Here, representativeness of certain coincidences or co-occurring events, like the building of 5G infrastructure in urban spaces concurrent with the density of COVID-19 cases in urban spaces, trumps competing explanations. This gives the appearance of such co-occurrences being more probable than their component events.

Correlations are detectable in any number of substantively unrelated phenomena (Vigen, 2015). The problem is exacerbated by data type, and researchers are not immune to the trap of spurious correlation. Time series data, for example, often return inflated correlation effect sizes and inflated t-statistics due to the presence of serial correlation (Shumway and Stoffer, 2017). This was particularly evident in a number of studies linking air pollution and COVID-19 infection (Zhu et al., 2020), which insufficiently account for the confounding effects of multiple variables (Travaglio et al., 2021). For panel data, problems with the addition of cross-sections have often led researchers to erroneous conclusions on the presence and strength of effects (Green et al., 2001). In the sections below, we discuss some 'functional' confounders of geographical correlation such as the modifiable areal unit problem. Thus, it is important to be clear on the distinction between observed and substantive correlations – the latter of which requires detailing an appropriately theorised causal mechanism. As to the latter, there is no physical science basis for the alleged correlation between 5G infrastructure and COVID-19 cases. Electromagnetic radiation at such transmission frequencies does not potentiate or transmit viruses, and there is limited evidence of its role in real or perceived health effects (Broad, 2019). Yet narratives like this are sustained in the face of historical cases of governments orchestrating secretive health conspiracy theories on their own citizens. Examples include programmes like the Tuskegee syphilis experiment run by the U. S. Public Health Service, or the poisoning of alcohol with methanol during prohibition (Heller, 2014; McGirr, 2016). This history may foment medical mistrust among vulnerable populations (Bogart et al., 2016; Cormack et al., 2019).

Distrust in government is rooted partly in past atrocities, as well as state "secrecy" as one of the dominant "predispositions that drive those beliefs" (Uscinski and Parent, 2014, p. 76). It is here that distinguishing between conspiracsm and conspiracy theory is useful. Conspiracism is a conspiracy without a foundational theory; it is an assertion, and is more common among the sound-bite listing discourses verbalized by its adherents, posited as if logical connection and meaning precedes the phrase (Muirhead and Rosenblum, 2019). Conspiracy theories on the other hand are "an *explanation of historical, ongoing, or future events* that cites as a main *causal factor* a small group of powerful persons, the conspirators, acting in secret for their own benefit against the common good" (Uscinski and Parent, 2014, p. 32 emphasis added). Correlating COVID-19 with 5G is thus a theory, as there is an identified narrative connecting the correlated entities, which acts as an explanation. For many believers and espousers, however, this is not a theory, but a fact. Conspiracy theories are not only about arguments over who is empowered to define, truth, but who may be defined as protagonists and antagonists—the 'people' or the elite scientists, policy makers, or corporations. When we write of conspiratorial thinking and ideation, we are referring to a predisposition that (Enders et al., 2020, p. 851) define as "a style of reasoning about the political world and our place in it … a 'perceptual screen' through which information is filtered and the world is interpreted".

In the following sections, we consider some principles of explanation in human geography, both as a means of interrogating the basis of conspiracy theory correlation, and to advance critical tools for their further deconstruction (Swami et al., 2014). We consider these along three related headings: social causality (principles of methodology governing causal reasoning), spatial causality (the interpretation of ecological correlation), and causal complexity (effect detection and effect size specification). Thus, we focus our discussion on conspiracy theorists' use of data, on the causal logics underpinning their understanding of how social entities are connected, and how they produce 'real' effects and patterns in the social world. Geographical correlation has an intuitive appeal in this respect, in a way that correlations between institutional properties do not. The visibility in space of communications infrastructure and COVID mitigation measures makes it more intuitive to assert a correspondence between these than, for example, abstract properties such as inequality and social capital (Wilkinson and Pickett, 2009). But the units that form the basis of geographical data structures (urbanities/conurbations, electoral divisions, economic zones) are also social and institutional artefacts. Both the contingent nature of geographical data – specifically ecological units – and associated technical issues specific to spatial data make interpreting meaningful correlations more difficult still. Whilst this renders the need for careful causal pathway theorising more important, conspiratorial thinking is atheoretical in this regard, as disparate events are connected in time and space, without any underlying theory of system. For geographical correlations, there are technical properties that make ecological correlations more visible (such as that described by the modifiable areal unit problem), and theoretical issues in understanding how social entities are constituted and how they exert causal forces on one another. Finally, we consider the implications of data democratization for the future propagation of conspiracist thinking – absent an appreciation of the unique technical and theoretical needs of interpreting geographical correlation.

3. Social causality: emergent properties and causal processes

From the above, we see how conspiracy theorist explanation thrives for large-scale, significant social events, when interpreted by groups with characteristics conducive to patternicity such as powerlessness (Whitson and Galinsky, 2008; van Prooijen, 2016). The tendency to perceive causal connections between covarying phenomena is heightened when those outcomes are of large-scale significance, and where the interpreters hold beliefs sufficient to override the covariation principle (van der Wal et al., 2018, p. 972). Such explanations of outcome assume that patterns of causality are linear – in the case of 5G-COVID, that 5G technology (cause) is additively associated with COVID-19 cases (outcome) via the mechanism of powerful interests. But a more fundamental question concerns the constitution of those large-scale social properties that are often the focus of conspiracist thinking –the distribution of power or technology, and those significant properties of human settlement such as population density, affluence and deprivation. Conspiracy theory narratives are typically absent an appreciation of key processes shaping socio-spatial outcomes, such as: (1) the emergent nature of outcomes at the macro level, and their production from, yet irreducibility to, the complex actions of individuals, and (2) the non-linear nature of processes that shape the phenomena we, as social scientists, capture at the empirical level.

A central problem of explanation in social science is the relative role of structures versus individual agency in the shaping of social life (Archer, 1995; Healy, 1998). Several such shaping processes are described at a high level of generality by heuristics such as path dependency or institutional lock-in/convergence (Mahoney and Thelen, 2009). Here we encounter a problem in communicating the logic of geographical analysis. Fundamental social-shaping processes are largely 'hidden' by the minutiae of everyday life and the time-spans on which social change occurs, yet their consequences are everywhere evident. Systems of governance, for example, are shaped by their historical and geopolitical contexts, which in turn influences their capacity for change, or limits of adaptability (Duit and Galez, 2008). In short, there are structuring processes at work at all levels of human social life - detectable to the analyst, but largely invisible to the individual. It is thus one of the key challenges of social science to explain such patterns in human behaviour and its spatial character, through abstract mechanisms – theoretical statements that summarise or capture relationships between entities in the social world, and explain how they generate 'real' effects (Sayer, 2000).

But this is also an important reason why public communication of the explanatory reasoning of behavioral scientists is difficult, dealing as we do in abstract properties, and explanation of phenomena in terms of largely 'hidden' generative processes that are complex and multicausal (Walby et al., 2012). Articulating how we reason the connection between individual behaviour and social structure is therefore key to interrogating the underpinning logic of conspiracy theories, as the latter is typically absent an appreciation of the extent to which patterns in the observable world are driven by underlying – yet ultimately 'hidden' – socio-spatial processes. One way to make sense of how regularities and patterns in the social world emerge from the seemingly complex actions of individuals is by viewing them as emergent properties. Emergent properties are not readily reducible to their constituent parts, and the emergence problem is well documented across the social sciences (Byrne, 2002; de Haan, 2006; Duit and Galez, 2008; Roberts, 2006; Sawyer, 2005). It describes the extent to which collectively observed properties are reducible to the actions of individuals, or conversely, whether macro-level properties can be 'aggregated up' from micro-level behaviour. This is a key issue in geographical analysis, as geographers frequently assert that there is indeed something scientifically meaningful about analyses conducted on aggregate data. 'Emergent properties' are those phenomena we observe at the empirical or 'real', as per critical realism (Bhaskar, 1997). By virtue of their emergent nature, they are complex in the sense that, as higher-order phenomena, they are irreducible to the micro-actions of the agents that produce them (Sawyer, 2005). Crucially, it provides a basis for the analytical autonomy of structural variables – a key question considered below in the use of ecological units in geographical analysis. It also makes causal explanation considerably more difficult by viewing social phenomena as the outcome of multiple interacting processes, which may, depending on their constitution, be more or less amenable to different types of measurement (Harvey and Reed, 2004). In the case of COVID-19 transmission, this includes not only empirical properties of human settlement such as density and connectivity, but also nationally specific and potentially unobserved predictors of compliance linked to belief in the efficacy of protective measures (Clark et al., 2020, p. 79).

Appreciation of emergence is thus essential to understanding how social properties such as technological diffusion – and their apparent correspondence with aspects of COVID – can arise independent of conspiratorial intentionality, as a result of commonly understood macro-geographical processes. One such process, for example, is that of agglomeration. Industrial clustering has long been recognised as a key process shaping regional economic character, and this is often intentional in cases where states enact policies conducive to attracting industries in regional agglomerations (van Egeraat et al., 2016). These processes can become autopoeitic or self-reproducing in conducive circumstances (Alhadeff-Jones, 2008). In the case of urban agglomerations, their characteristics are shaped by variables common to both transmissibility and technological connectivity, such as population density and predominant economic activity (Fang and Yu, 2017). The co-incidence of COVID-19 and 5G is further explicable in terms of heightened infrastructure demands of remote working (Beech, 2020), thus reinforcing the covariation of both. Issues of complex causality and the constitution of social properties are lost in narratives emphasising a linearly-causal world, where entities are related to each other via 'simple' causal processes (such as conspiracy theories of infection orchestrated by powerful interests). It is not the potential presence of covert interests in conspiracy theory narratives that is at issue here - powerful interests can, and do, induce rapid change, and have been responsible for catastrophic events as discussed above. The issue is with the assumed linearity of such change processes in the causal logic of conspiracy theories. Absent a concept of emergence, we are left with the appearance that regularities (technical diffusion) are a linear function of the intentions of powerful interest groups, and that the causal pathways from intent (social control) to effect (5G technology location) are linear.

4. Spatial causality: ecological correlation and spatial data structures

Whilst emergence poses several challenges to ontology in geographical explanation, it also draws attention to the units of analysis involved in empirical analysis. For human geographers, this is often the ecological unit of analysis, or sets of point data distributed over a defined plane. One issue invoked with such data structures is the risk of the ecological fallacy – the ascription to individuals of tendencies established at a higher level of aggregation or analysis. COVID "contagious conspiracism", as we have seen above, is often inherently spatial in its construction, referencing the characteristics of areas (i.e. COVID-19 incidence or base mortality), or the distribution of points (i.e. the location of 5G infrastructure) (Sturm and Albrecht, 2021, p. 2). Specific problems of interpretation and explanation arise when dealing with spatially aggregated data, and ecological data are fraught with several logical pitfalls. As social scientists, we are often forced to reconcile this potential risk with the assertion that there is indeed something scientifically meaningful to analyses conducted on spatially aggregated data. This is made difficult by the fact that the geographical units utilized by analysts are often the product of human whims, and whilst some may bear some inherent relation to the surrounding social landscape, others are less intuitive (i.e. gerrymandered electoral districts, or straight-line colonial borders). Despite this, ecological correlation (here used as shorthand for analyses conducted on area-level data) is frequently, and productively used in several areas of geography and comparative political economy (Flaherty, 2018). For deconstructing COVID conspiracy theories, this is important as the absence of recognition of issues in the use of data at various levels of aggregation opens a window to ascribe motivations to individual action that are either impossible to assert from the level of analysis employed, or explicable/detectable only at the collective level.

Thus, it is not an inherent issue with the use of spatial data or ecological units that renders ecological correlation problematic, but rather its interpretation. Indeed, the disconnect between correlations at the individual and ecological levels has long been recognised in the statistical literature (Robinson, 1950). Correlations derived from ecological units (i.e. neighborhoods or electoral districts) cannot be assumed to describe relations in general between properties at the individual level, in either magnitude or quality (Openshaw, 1984). The intractability of the ecological fallacy can be demonstrated with reference to the ongoing lack of a consistent causal mechanism linking, for example, inequality to human ills such as homicide, premature mortality, crime, incarceration, and drug use (Goldthorpe, 2010; Layte and Whelan, 2014). Indeed, causal pathway attribution in studies based on ecological or otherwise aggregated data is often highly contested. Overcoming it requires careful theorising and reasoning of effect pathways, rather than technical fixes or analytical sophistication (Brunsdon and Comber, 2020, p. 90). The tendency to infer lower-order associations and motivations is understandable if one remains at the level of the empirical only, as ecological correlation is inexplicable without an underlying theory of causality. Once we appreciate both the contingent nature of geographical units, and the abstraction required to account for macro-level phenomena, the allure of the uni-causal conspiracy theory can be supplanted with an appreciation of its causal complexity. This appreciation is typically absent from conspiracist thinking, which often remains at the empirical only.

Consideration of some potential technical pitfalls of ecological analysis are also revealing. Formally identified by Gehlke and Biehl (1934) and elaborated by Openshaw (1983), the modifiable areal unit problem (MAUP) describes the tendency of the size of correlations to increase as area size increases. More broadly, it identifies how statistical summaries are influenced both by the size and shape of geographical units. Yet experimental studies also show how the tendency toward patternicity is heightened for phenomena of larger scale and social significance (van der Wal et al., 2018). In others, the size of the issue in question is found to be a direct predictor of its attribution to conspiracy theory origins or causes (van Prooijen and van Dijk, 2014). It is therefore tempting to draw some parallels between such scale effects in both cognitive disposition and geographical correlation, although this is highly tentative. If, as the emergence problem suggests, there is a risk of committing the ecological fallacy when projecting the findings of spatial associations to populations of individuals, does that mean such exercises are inherently null? Not exactly – it is difficult to deny that collective properties have causal influence (think of the effect of educational or religious systems on everyday behaviour and decisions), but it does mean that considerably more theoretical work is needed to articulate the causal connection between, say, the correspondence between 5G infrastructure location/network density, and COVID-19 incidence. Herein lies a problem for conspiracy theory reasoning. Geographical data have considerable explanatory appeal – lives are structured in space, and the spatial character of human behaviour is often more intuitive than the causal forces exerted by more abstract entities such as political institutions or educational systems. Humanity articulates its sense of ontological security in terms of places – making NIMBYism one of the more powerful motivational forces to political action than ideology – but the 'missing piece' of causal theorising is absent in conspiratorial thinking. The intuition of the spatial is present, but the causal mechanism is not – and indeed conspiratorial thinking thrives partly due to the absence of appreciation of the inherent complexity of causality. We address this in the following section.

5. Causal complexity: autocorrelation and spuriousness

Along with the theoretical challenges of reasoning causal processes, there are additional technical issues that render certain types of data more difficult to derive 'true' effect sizes from. In quantitative studies, there are often competing methods of effect size and standard error calculation, for example. These are not merely issues of public misinterpretation or 'specialist vs non-specialist' – they are ongoing debates within academic research on the interpretation of quantitative data, such as the correspondence between statistical and substantive significance (Ziliak and McCloskey, 2008; Wasserstein and Lazar, 2016), or the robustness of existing research findings to replication or re-specification (Aarts et al., 2015; Wilson and Butler, 2007). Some data types carry inherent risks. Time series correlations often return inflated effect sizes and standard errors due to serial correlation (Flaherty, 2018). Spatial data are similarly prone to the phenomenon of spatial autocorrelation, where values of adjacent units may be correlated as a result of their proximity. It is an inherent aspect and artefact of human population data, arising from the geographically ordered nature of human settlement (think of the locally clustered nature of crime rates, deprivation indices, social housing densities, or industrial sectors). But it is a particular concern for spatially ordered data analysis, as proximate or locally clustered units of similar value can give rise to misleading estimates of global effects, bias model diagnostics, or render local deviations from global averages invisible (Brunsdon and Comber, 2015). As such, it is both a 'nuisance' parameter (to the extent that it 'interferes' with the accurate determination of geographically varying effects), or more importantly a 'missing variable indicator' or 'spatial process mechanism' (Griffiths, 2020, p. 11) pointing toward important, potentially unobserved processes at work in producing the effect in question (such as infection rates, or 5G coverage).

What does this mean for interpreting the distribution of COVID-19 infection, 5G infrastructure, and their correspondence? Defining the problem in a geographical context requires several considerations: (1) recognizing that the distributions of both variables have a geographical character, in terms of their observed spatial distribution, and the social processes underpinning that distribution; (2) arising from this, understanding how the spatially autocorrelated nature of the data introduces greater potential for 'positive' findings of association and signature spatial distribution - absent an appreciation of how such geographical patterns are produced through processes such as agglomeration, and their technical implications for measuring effects; and (3) identifying that the spuriousness of 5G-COVID is a product of both technical issues of data, and poor specification of causal process. The urban-geographical character of both COVID-19 and 5G is attributable to factors such as urban connectivity and population density, which are key factors in urban economic specialization and growth (Lai et al., 2020).

They underpin demand for connective technologies, but population density is also a key predictor of morbidity and mortality (Kodera et al., 2020, p. 7). Thus, to the first condition, we may expect to detect a characteristic geographical distribution to both variables, independently arising from shared sets of determinants characteristic of urban areas. To the second, the potential presence of spatial autocorrelation in both 5G and COVID-19 means both theoretical attention (to the processes underpinning the geographical clustering of both), and technical attention (to the inflated risk of erroneous findings) is warranted. Coupled with the cognitive frames of conspiracy theory reasoning, the *inherent* risk in geographical phenomena such as this merely heightens the likelihood that the conditions of errant data, patternicity, and conjunction will be satisfied to the observer.

Together, these produce the spurious observation of correlation, and determination of causality. It is important to bear in mind that spuriousness is not a technical issue alone – the risk can be reduced by including competing explanatory variables, or altering model specifications to account for effects such as mediation, but it is ultimately a theoretical endeavour. Some of this is elementary to students of human geography – Tobler's first law governing the relatedness of proximate entities, for example, being widely understood (Flaherty, 2020, p. 4; Miller, 2004; Tobler, 2004). Yet the tendency to observe correlation is not merely cognitive bias – it is fast becoming inherent in the age of big data. For sufficiently large datasets, it is possible that spurious correlations may form the majority of observed correlations, which will 'naturally' arise in large datasets as a function of their size, rather than the nature of the data (Calude and Longo, 2017, p. 607). Thus, as the age of big data advances, the demand for theoretical care in specifying causal mechanisms rises accordingly. In the case of 5G-COVID, this requires care in detailing the agglomeration processes that give rise to the signature distributions of both, and the causal pathways – the substance of urban geography – that permit their admissibility as scientific statements. Yet as suggested above, conspiratorial thinking thrives in the absence of behavioral-geographical theories linking human decisions (i.e. urban planning around housing, or industrial/technological development policy) to spatial outcomes (5G infrastructure location, residential density, and connectivity). Without a cursory sense of the inherent nature of these confounders to geographical analysis and reasoning, conspiracy theories are unable to see how apparently meaningful correlations and patterns like this can arise (and do arise in many aspects of life and data) without any real relationship to each other.

6. Big data geopolitics and democracy

Why is the case of COVID-5G conspiracy theory important to challenge? Because urban geographical health data are prone to exhibit these kinds of relations and distributions, we should expect conspiracy theories to develop more, equally damaging correlations using errant data, patternicity, and conjunction logical fallacies. But unlike previous studies based on decontextualized experimental work, we argue that geopolitical context matters. Whilst these valuable studies show education and powerlessness as predictors of conspiracist beliefs (van Prooijen, 2016; Whitson and Galinsky, 2008), in the U.S., perceived powerlessness in the face of government has become a rallying point for marginalized groups with capacity for organised violence. The COVID-5G correlation is but one item in the current repertoire of conspiracy theory narratives asserting sinister motivations to government. There is also a contradiction here, as the state and academic-led moves toward data democratization – production, governance, but also public access to data – could make it easier and more likely for conspiracy-inclined groups to forward and defend claims like this with the apparent authenticity of statistical rigor. But the risks presented by urban geographical health data are not limited to such groups alone. Data is not neutral and biases in data analysis exist at the level of governance (McMillan et al., 2016, p. 2936). As demonstrated through the examples in this paper, data quality and analytical approaches to health questions are often not fully considered by many governments. This can perpetuate harmful approaches to health governance of vulnerable members of society, including the poor and racially marginalized (Cormack et al., 2019). How can we reasonably hold citizens and conspiracy theorists to a data quality standard that many health governance bodies themselves have failed to meet?

Similarly, the increasing push towards public data access will be limited as long as private companies are permitted to withhold data for reasons of commercial secrecy. Governance mechanisms for health purposes are increasingly being tendered to corporations whose data practices operate within a black box. For example, with COVID-19 pandemic tracking health apps, governments that partnered with large corporate tech firms have largely failed to publish code for their apps (Leith and Farrell, 2020). State transparency has little value if the data processing infrastructure rests in the hands of industry tech and without such transparency, and as a result urban conspiracy theory spatial analysis will find further grist and motivation. Moreover, the questions of equality and fairness raised by earlier government health experiments have not been resolved. If government health data science relies on opaque, biased data sets and analytical methods, then the risks of discrimination are still very real today. This presents not just the opportunity for conspiracy theorists to misuse data but also validates any scepticsm about the ways their health-related and otherwise personal data is being collected and processed around them without their knowledge or consent. Until our governments can learn to look at data sets critically for the purposes of equitable and fair governance, how can we reasonably hold those living under state governance to a higher standard?

7. Conclusion

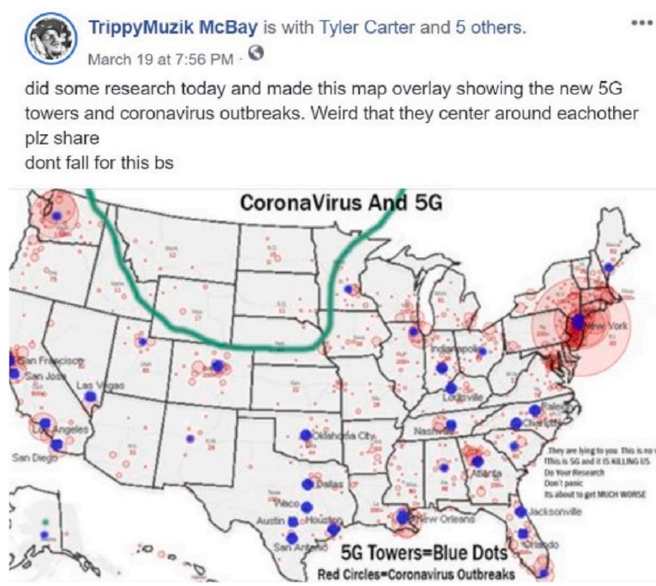
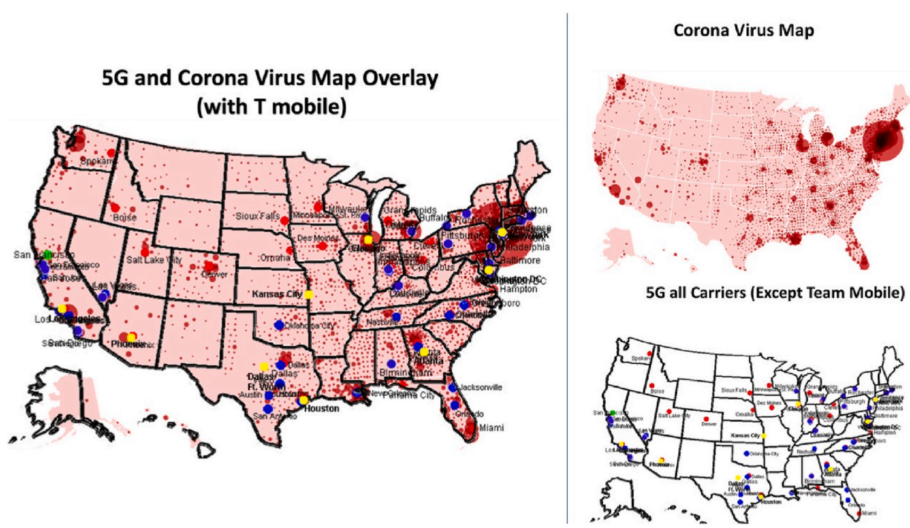
Conspiracy theories are of serious consequence to civic and public wellbeing (Uscinski, 2019). Conspiracy theory interests around anti-mask, anti-vaccination, and now 5G, are real and imminent threats to public understanding and trust of medical science and policy (Wang et al., 2019; Romer and Jamieson, 2020). We have seen how the QAnon conspiracy in the U.S. congealed around a broad alliance of disparate conspiracy theories, but also several white supremacist and insurrectionary groups that invaded the U.S. Capitol building in Washington on January 2021. Adherence, belief, and even exposure to conspiracy theories is associated with declining civic engagement as well as racial and socio-economic prejudices and violence (Jolley and Douglas, 2014; Bartlett and Miller, 2010). Thus, understanding conspiracy theories and theorists is critically important to the integrity of democracy and recovering the anti-scientism that has blighted many countries over the past years. 5G-COVID is an instructive case on several fronts, as an exemplary case in the importance of sound geographical reasoning, but as a demonstration of how – through absence of sound methodology – belief in the validity of data-driven propositions can thrive. Thus, whilst the above can – and should – serve a pedagogical function in equipping geographers with the necessary logical tools, it can also inform as to where critiques of conspiracy theory-driven data use should be applied. Crucially, the probabilistic laws and analytic thinking we present above has been shown to reduce the belief in conspiracy theories (Swami et al., 2014).

In this paper we explore COVID-5G conspiracy theorists' use of data, mishandling of basic principles of analysis, and poor appreciation of causal complexity. We emphasise three methodological areas that deal both with the technical aspects of geographical data and its handling, and the interpretation of effects and causality in spatially correlated phenomena: social causality and the interpretation of causal processes, spatial causality and ecological correlation, and causal complexity in effect detection and specification. Coupled with known tendencies toward patternicity in conspiracist thinking, we argue that these specific issues in geographical data analysis render phenomena such as the perceived correlation between COVID and 5G especially vulnerable to conspiracy theory attribution. Absent an appreciation of the technical properties of such data, and an understanding of how causality between social entities is exerted, such attributions are more likely. In detailing this, we hope to have provided a template to interrogate conspiracy theorists' uses and interpretation of data and offered a caution of the potential for their future misuse in an age of big data democratization. In sum, we offer a basis for medical and spatial analysis practitioners, public, and media to interrogate the foundational basis of the spurious correlation between 5G and COVID-19 cases. Further, we provide a caution against the potential for similar phenomena to be co-opted by conspiracy theory groups, to the detriment of both the public understanding of science, and potential compliance with public health policy.

Author contribution

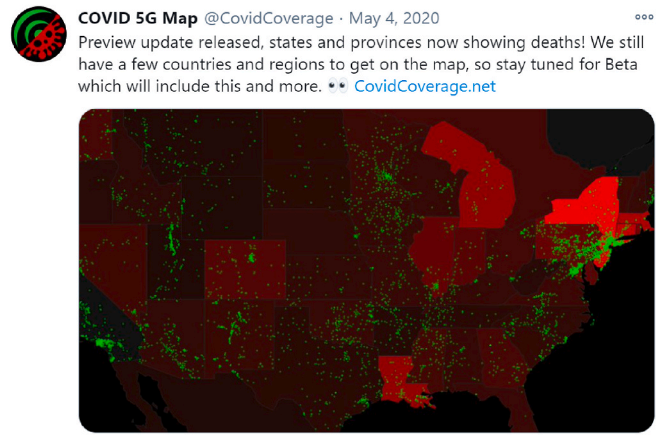
Eoin Flaherty: Conceptualization, Investigation, Resources, Writing. Tristan Sturm: Conceptualization, Investigation, Resources, Writing. Elizabeth Farries: Conceptualization, Investigation, Resources, Writing.

Appendix 1. Sample COVID-5G maps

Number	Source	Date	Notes	Image
1	Twitter and Facebook, Archived	March 19, 2020	One of the original trending COVID-19-5G maps, this map uses AT&T 5G tower data only (378 cities in 34 countries contained 5G-capable infrastructure in January 2020).	
2	Reddit	April 3, 2020	Reddit post to r/research, weighted icon COVID-19 cases overlaid with 5G carrier locations (AT&T, Verizon, T-Mobile, and Sprint).	
3	Twitter	May 4, 2020	Graphic claims to be composed from heatmap of COVID-19 cases and 5G network coverage. Associated	

(continued on next page)

(*continued*)

Number	Source	Date	Notes	Image
			website (now inactive) claims to be from a group of developers working on a site that overlays minute data of COVID-19 and 5G towers. Map appears to use Bing COVID-19 tracker data and maps.	
4	Twitter	March 12, 2020	Map tweeted by Manchester Councillor, Kenneth Dobson.	

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