Improving Longitudinal Research in Geospatial Health: An Agenda

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Abstract

All aspects of public health research require longitudinal analyses to fully capture the dynamics of outcomes and risk factors such as ageing, human mobility, non-communicable diseases (NCDs), climate change, and endemic, emerging, and re-emerging infectious diseases. Studies in geospatial health are often limited to spatial and temporal cross sections. This generates uncertainty in the exposures and behavior of study populations. We discuss a research agenda, including key challenges and opportunities of working with longitudinal geospatial health data. Examples include accounting for residential and human mobility, recruiting new birth cohorts, geoimputation, international and interdisciplinary collaborations, spatial lifecourse studies, and qualitative and mixed-methods approaches.

Highlights

- Geospatial health studies can be limited by using spatial and temporal cross sections.
- Geospatial longitudinal studies can better capture spatiotemporal dynamics of health.
- We summarize the challenges and opportunities to improve research and collaboration.
- For example, studying residential mobility, life course exposures, and geoimputation.

1. Introduction

In this short paper, we focus on a forward-looking agenda for longitudinal research in geospatial health. We especially focus on ways that researchers can address the methodological limitations and the research questions which may be increasingly pressing in the near future. Geospatial studies in health research are often limited by utilizing spatial and temporal cross sections that do not capture the true spatiotemporal dynamics (e.g., change in residence, or in covariates) of longitudinal health exposures, behaviors, and outcomes. There is typically greater uncertainty in exposures and behaviors in longitudinal studies, although the outcomes can be more reliably measured (Delmelle et al., 2022). Longitudinal analyses more accurately capture the dynamics that drive health outcomes throughout the lifecourse of at-risk populations. This is particularly important as ageing populations, human mobility, increases in non-communicable diseases (NCDs), climate change, and endemic, emerging, and re-emerging infectious diseases all require longitudinal analysis to fully capture the dynamics of health outcomes and risk factors. While many useful longitudinal health datasets are available, many are analyzed without linking them to spatially-explicit data (e.g., maps & geographic information system (GIS)-ready data such as administrative boundaries). Disregarding the nexus between health and place and not accounting for the spatial processes that underlie data may be hindering scientific discovery and reducing the potential future impact of longitudinal public health research.

Studies that lack spatial data, methods, and visualization can create uncertainty and result in a theory-practice gap. Integrating spatial analysis in longitudinal health research can facilitate targeted interventions and improve public health policy and decision-making by identifying specifically where at-risk populations are located and what is influencing disease risk and exposure, particularly the 'wider determinants' of health across the lifecourse. More formally, these concepts fall under the umbrella term of "spatial epidemiology" (or 'health and medical geography'), which is "the spatial perspective into the design and analysis of the distribution, determinants, and outcomes of all aspects of health and well-being across the continuum from prevention to treatment" (Kirby et al. 2017). In a recent editorial in Population, Space and Place, Keenan et al., (2020) state that "we need high-quality, representative data capable of capturing multi-scalar longitudinal processes". Longitudinal datasets have been collected and updated across the world, while research comparing the longitudinal impacts on health outcomes across several countries/regions has recently increased in the literature, such as neighborhood perception and depression among older adults (Baranyi et al., 2020); and neighborhood disadvantages and all-cause mortality (Ribeiro et al., 2022). However, the datasets used in this research may not be generalizable nor capture the spatio-temporal processes that impact exposures and health outcomes across the study population(s) of interest. Furthermore, there is still a paucity of literature, and we encourage scholars to conduct new and improved research on spatial analysis of longitudinal data.

2. Challenges and Opportunities

Uncertainty, Missingness, and Mobility

Although there are a variety of available longitudinal public health datasets, they are typically not explicitly linked to spatial data, which can be due to lack of spatial expertise. Certain longitudinal datasets may require the data source/governors to link the non-spatial data to spatial data after approval. Otherwise, researchers may be tasked to link the longitudinal datasets to the necessary spatial data themselves. Whomever conducts the linkage, it is important for researchers to have knowledge of, and be able to address specific issues related to longitudinal spatial research. For example, challenges of time-varying Census data (Jung et al., 2019; Delmelle et al., 2022) and the changing dynamics of the study cohort during follow-up observations. Administrative boundaries, background population, social vulnerability indices, and environmental variables will change over time, and this should be reflected and updated when linking geographic data to longitudinal health data. Furthermore, uncertainty may be present in many aspects of the study, from spatial and attribute errors created during data collection and processing, temporal uncertainty such as delay between exposure and disease onset or delays in reporting, margin of errors in Census data, and missingness in follow-up measures in longitudinal cohorts. There may also be specific issues of ethics and confidentiality associated with records showing survey respondent locations over time.

A large number of studies tend to use neighborhood measures without carefully choosing indices and being mindful about more pertinent variables and theory regarding the nexus between health and place (e.g., Normalized Difference Vegetation Index (NDVI) as a measure of greenspace without accounting for amenities, walkability, and utilization). This is especially a challenge when dealing with longitudinal exposures of greenspace/bluespace and health outcomes where current measurement of these exposures are likely to not be accurate as they change over time. Next, there is a pressing need to study vulnerable and underrepresented groups and addressing environmental justice issues in a particular study area across time. For example, homeless populations and traveler communities are often excluded because their locations are not fixed to a particular address. We suggest mobile-device or GPS tracking and public participatory mapping to better study their activity spaces and potential short- and long-term exposures (Semborski et al., 2022). Furthermore, other underrepresented groups should not be dichotomized into aggregated groups if possible, such as LGBTQIA+, subgroups of chronically ill (e.g., various mental illnesses), and nondominant religions, retirees (Abo-Zena, 2010).

Another common issue is attrition/loss to follow-up which is a common occurrence in longitudinal data sets and is amplified by the introduction of spatial and temporal dimensions. Delmelle et al. (2022) provide numerous examples and suggestions to address and account for the inherent uncertainty in geospatial health, including longitudinal studies. One suggestion is incorporating longitudinal weights which helps to reduce attrition bias (Vandecasteele and Debels, 2007). Another suggestion is geoimputation, which can reduce spatial and temporal missingness (Mennis et al., 2018). Furthermore, multiple imputation is a common technique to increase completeness of longitudinal data sets which estimates multiple possible values for missing data points, accounting for uncertainty by computing standard errors around the estimations (Spratt et al., 2020). In general, utilizing geoimputation and classical imputation techniques can improve sample sizes, completeness, and spatiotemporal resolution of the cohorts being analyzed in longitudinal studies. Structural Equation Modeling (SEM) is also another method that can address missingness by applying full information maximum likelihood estimation (FIML), essentially modeling estimates based on the maximum amount of available information (Lee and Shi, 2021).

A fourth issue is accounting for both residential and daily human mobility, which may greatly influence individual(s) exposure, healthcare accessibility, social determinants of health, and subsequent health outcomes throughout a longitudinal study (Kirby et al., 2017). Accounting for residential histories can more accurately capture lifelong exposures and the nexus between health and place. Not all longitudinal studies on health outcomes control for residential history, especially not over long periods (e.g., across the lifecourse). There is also the problem of longitudinal studies of variation in health among small areas, which may not control for inward and outward migration (Norman et al., 2005; Lomax et al., 2013). Although this is not a major issue among studies with shorter follow-ups (e.g., Understanding Society[1]), it can be problematic

[1] https://www.understandingsociety.ac.uk/

with much longer follow-ups (e.g., annual, biennial, etc.). Also, we usually do not know how long participants were living at their addresses registered during the follow-up waves. We strongly suggest collecting continuous residential histories. For example, with appropriate permissions from the data governors, these data can be collected from data kept by general practitioners, health departments, and other administrative records (Baranyi et al., 2020; Raaschou-Nielsen et al., 2022). Furthermore, accounting for human mobility (e.g., daily activities, migration, etc.) with GPS (Global Positioning System) tracking, cell phone records, social media data, etc. can improve the understanding of transmission dynamics, healthcare seeking behavior, accessibility to various resources, among others (Kwan, 2012; Wesolowski et al., 2012; Buckee et al., 2020). For instance, a recent New Zealand based study used nationwide mobile phone movement data to quantify the effect of an enforced lockdown on population mobility by neighborhood deprivation highlighting how curtailed movement may have exacerbated underlying social and spatial inequalities (Campbell et al., 2021). In short, people are not static, and we need to develop the wider use of methods that better capture the mobility patterns to improve our understanding of exposure, disease transmission, and influence of place on health outcomes.

Improving Longitudinal Cohorts

Existing longitudinal cohorts can be improved by linking area-level data in a consistent manner across many longitudinal cohorts. For example, the United Kingdom Longitudinal Linkage Collaboration, where environmental data is currently being linked across 20 UK longitudinal studies (Flaig, 2022). New birth cohorts could also be developed to collect high-quality geographical data, such as the Environmental influences on Child Health Outcomes (ECHO) cohorts in the United States (Jimenez et al., 2022; Starling et al., 2022; Mein et al., 2022). Instead of relying on retrospectively linking historical data about individual mobility at earlier life stages (which contains limitations such as recall bias), these cohorts could be set up from the beginning for spatio-temporal analysis (e.g. basic geographic data, commonly researched area-level data, etc.). A more time-effective approach is assembling new cohorts solely from administrative data, which is a promising way forward especially if the data can be collected retrospectively[2]. Finally, it is critical to create and update longitudinal surveys to be as parsimonious as possible to minimize participant fatigue and dropout.

[2] https://calls.ac.uk/2017/03/30/new-1936-birth-cohort-study/

Interdisciplinary and International Collaborations

The COVID-19 pandemic has highlighted the notion that "public health is global health". Scientists and scholars around the globe contributed to our understanding of disease transmission, mitigation, and prevention from numerous disciplines. While the power of geospatial science was highlighted throughout the pandemic, interdisciplinary and international collaborations have been on full display. Whether it relates to infectious or non-communicable diseases, public health research can benefit from expertise of geographers, computer and data scientists, engineers, medical doctors, sociologists, psychologists, and others; while collaboration among experts in these fields can vastly improve longitudinal area health research. In addition, the UK-US joint statement on deepening the data partnership issued in August of 2021 aims to facilitate "cross-border data flows while maintaining high standards of data protection and trust" and "open and inclusive engagement" with international partners (UK Government, 2021). Similar health outcome data are available in both countries, such as age-related conditions (e.g. frailty, cognitive decline), behavioral risk factors (e.g., obesity, substance abuse, physical inactivity), ambulatory medical care, self-reported health status, infectious disease outbreaks, among others. Furthermore, healthy aging can be a major area of 'cross Atlantic' collaboration, since both countries (and most of the developed world) face rapidly aging populations, shifting disease burden to chronic, labor-force shortages, increasing healthcare expenditures, similar patterns of geographic health disparities that follow trends of de-industrialization and social spatial disparities. As a result, improved cohorts (e.g., life course surveys; health behavior, knowledge, and attitude variables) and fine-level geographic data are necessary to address the increased pressure of aging on healthcare systems. While aging is a pressing issue around the developed world, which should certainly be a focus for these interdisciplinary and international collaborations, it can be argued that such initiatives are vital for all longitudinal research. Researchers must also acknowledge the challenges and limitations of interdisciplinary and international collaborations, such as differences in (1) sociocultural and demographic populations, (2) survey designs, (3) availability of comparable data for different geographical regions, and (4) healthcare systems and equality of access, which all can influence the outcomes.

A final challenge is the different analytical traditions and what we understand as best practices in different disciplines. In psychology, analyzing longitudinal observational data in a

Structural Equation Modeling (SEM) framework is considered the golden standard, while in epidemiology studies with repeated measurement more often rely on mixed effects models. Another example is whether and how to deal with multiple comparison: while in some disciplines correcting for multiple comparison (e.g., Bonferroni correction, False Discovery Rate adjustment) is seen as best practice, in other disciplines it is less often done. Furthermore, causal inference techniques have been widely used in non-spatial disciplines, but recently have been implemented as spatiotemporal causal inference frameworks and can address the complex correlation structures in longitudinal spatial data (Reich et al., 2021).

Putting "Spatial" in Lifecourse Epidemiology

A promising subspecialty of longitudinal health research is lifecourse epidemiology, which "studies how socially patterned exposures during childhood, adolescence, and early adult life influence adult disease risk and socioeconomic position, and hence may account for social inequalities in adult health and mortality" (Kuh et al., 2003). This is an especially important approach as this is able to capture cumulative exposure which starts at conception and continues throughout childhood to adulthood. Only recently have we seen formal paradigms that address these challenges under a spatial lens, such as "The Lifecourse of Place Approach" (Pearce, 2015; 2018) and "Spatial Lifecourse Epidemiology" (Jia, 2019). Both aforementioned paradigms address similar objectives of improving lifecourse cohorts and analysis in geographic studies. Recent studies have utilized these spatial lifecourse paradigms to study human mobility and long-term care homes during COVID-19 (Chen and Steiner, 2022; Kain et al., 2021); exposure of neighborhood deprivation over the lifecourse (Jivraj et al., 2021; Murray et al., 2021; Baranyi et al., 2022b); and the association between life course air pollution exposure and biological aging (Baranyi et al., 2022a). Although not completely new paradigms, they are underutilized and recently gaining attention in the literature, therefore, we encourage researchers to explicitly account for spatial in lifecourse epidemiological studies (Curtis et al., 2003).

Incorporating Qualitative and Mixed Methods

While the main focus of this paper is on the use of quantitative data to conduct longitudinal studies in geographies of health, we would also briefly note that there is a growing field of qualitative longitudinal research on health and health care (not limited to geographies of health specifically), which also offers important potential to improve our understanding of the determinants of health over the lifecourse. New paradigms can consider a "holistic" approach

(Desjardins, 2020), which essentially encourages a feedback loop between researchers, stakeholders, and study participants to maximize relevant and effective research questions and promote translational science from baseline to study finish. For example, this is the focus of a recently published major volume (Neale, 2021) which provides an overview that brings together insights from this field of research and showing the diversity of methods used and how conceptual and theoretical models framing different projects relate to practical aspects of methodology. Also, Adulv et al. (2022) carried out an extensive systematic survey of the literature in this field and examined 299 studies. They report on one limitation of this field where most studies focused on individual experiences which were followed over fairly short time periods (more than half covered periods of up to a year.) The authors also comment on the importance of the theoretical grounding of many qualitative studies, e.g., phenomenology and grounded theory are often used to frame the qualitative field of health research. They note the diversity of qualitative methods that are often used in combination, which they argue is one of the interesting aspects of this kind of approach.

As an illustration of these more general points relating to qualitative longitudinal research, we might consider a more specific example, viewed from a health geography perspective by Woodgate et al. (2017) who followed the experiences of individuals over 3 years in 40 families including children with complex care needs (CCN) living in a city in Canada. Data were collected using in depth interviews and photovoice techniques. The research demonstrated how "…the embodied spaces of children with CCN revealed that the decision-making processes relating to health and everyday life were complex and socially interconnected" (Woodgate et al., p11). This kind of study may offer strong potential to help inform the ways that quantitative studies are framed, in terms of the types of data collected, both on individual members of statistical samples and on the settings where they live and access health care. Another specific example is reported by Wright and Patrick (2019), in a study showing how governmental changes to welfare benefit regimes can have detrimental impacts on mental health of the recipients. They argue that their approach in combining data from separate longitudinal qualitative studies builds strength to their conclusions. Overall, there is a case to be made for developing stronger connections between quantitative and qualitative longitudinal research in geographies of health and wellbeing, and perhaps more research projects will be designed in future which bring together specialists in these different approaches to generate knowledge rooted in personal accounts of relevant experiences of diverse spaces, as well as statistical data on individuals and places.

3. Conclusions

This article provided some thoughts on key aspects of this subfield that require further future investigation; however, it is by no means exhaustive nor a panacea. We encourage researchers to work together to improve longitudinal data and research in geospatial health. We also need to be training the next generation of spatial life course researchers, who require a unique core cross-disciplinary training in geography, psychology, longitudinal statistical methods, life course theory, and mobility research. We hope to further stimulate discussion and facilitate new and novel collaborations across disciplines and geographic regions. Join us in improving this subfield of longitudinal research in geospatial health; if this is an area you are interested in and/or working in, please email the corresponding author to continue building this network across disciplines and international boundaries.

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