Received: 31 July 2020 | Revised: 21 January 2021 | Accepted: 4 April 2021

DOI: 10.1111/gec3.12566

ARTICLE

WILEY

Reconsidering movement and exposure: Towards a more dynamic health geography

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Funding information
GeoHealth Laboratory, Grant/Award Number: Ministry of Health, New Zealand

Abstract

Acknowledging a paucity of emerging research, and some variation by sub-field, the geographical measures of exposure used in health and medical geography have largely stagnated often focusing on residence-based ('static') conceptualisations to define an individuals mobility or exposure. Detailed spatiotemporal data, such as smartphone data, allow richer understandings of the influence of the environment, or more broadly of place, on individual health outcomes and behaviours. However, while researchers are increasingly aware of such 'dynamic' definitions of place these are seldom employed in empirical evidence. Moreover, there may be differences in mobility by population groups which has not to our knowledge been examined fully. The main aim of this article is to provide a critical review of progress in the conceptualisation of location in health-related geospatial research to understand the evolution of key concepts and to provoke the reader into considering the utility of a (more) dynamic health geography. We explore the origins of time geography, activity spaces, before moving to recent developments in the area of the exposome and the linked dynamic conceptualisations of exposure in health geography. To illuminate and operationalise findings from our review for readers, we provide a small case study to demonstrate how 'static' and 'dynamic' approaches differ. Moreover, we consider why understanding heterogeneity in mobility could be particularly salient in the field of health geography, and to the discipline of geography more broadly. To conclude, we help readers understand the practical considerations of data privacy, the process of data collection, data processing, and interpretation, and dissemination of findings to offer practical assistance for those who are grappling with 'dynamic' definitions of mobility and conceptualisations of exposure.

KEYWORDS
environment and society, GI science, health geography, mGeoHealth, quantitative methods

1 | BACKGROUND

The study of how place influences health is well established (Curtis & Rees Jones, 1998; Pearce et al., 2006; Rundle et al., 2016; Xu & Wang, 2015). However, it could be argued that methods in health geography have stagnated (Hobbs & Atlas, 2019) with measures often focusing on residence based conceptualisations ('static'), such as home address, to define an individual's mobility or exposure (Campbell et al., 2013, 2014; Cummins, 2007; Macintyre et al., 2002; Rosenberg, 2016a; Tobias & Cheung, 2003). Indeed, there is growing discontent in the health geography literature about the lack of appropriate conceptualisation of 'place' (Macintyre et al., 2002) or of the role of mobility (Morris et al., 2016). While, acknowledging some variation by sub-field, researchers are increasingly aware of 'dynamic' conceptualisations of place: but, these are challenging to employ as a method. While some scholars have progressed towards tracking the movement of people or changes in environmental exposures in both space and time ('dynamic'), a recent review of exposure to the retail food environment and obesity highlights many have not; 89.4% of all included studies (n = 113) used 'static' buffers or area unit-based metrics of exposure (Wilkins et al., 2019). Life course epidemiology has long recognized the role of time in long-term exposure effects, and that different exposures operate over people's lives and their residential history (Helbich, 2018). However, a persistent problem yet to be fully addressed, is the accurate estimation of the causally relevant geographic context for individuals (Kwan, 2012), also known as the Uncertain Geographic Context Problem (UNCoP) which has persistently challenged researchers trying to use 'dynamic' definitions of place. There is still a paucity of evidence that quantifies both the nature and extent of any such differences between 'static' and 'dynamic' approaches and explicitly relates these conceptualisations to environmental exposure. There is also methodological confusion about the most appropriate way in which to use 'dynamic' conceptualisations of place, mobility and environments, potentially explaining inconsistencies in study results (Liu et al., 2020).

1.1 | Time geography

While rarely discussed in current evidence, the concepts relevant for 'static' versus 'dynamic' measures have epistemological origins in the activity space and time geography literature. With respect to time geography, proximity to an exposure was in itself considered enough (Hägerstraand, 1970). However, Hägerstraand (1970) conceptualised the idea of a space-time path, the movements of a person through space and time simultaneously.

The 'activity space' concept is one example which moves beyond 'static' spatial units to a personalised exposure area (Perchoux et al., 2013). Activity spaces can be defined as the areas that people move within or travel through during their daily activities (Sherman et al., 2005). Nevertheless, health geography has (still) not integrated these ideas especially well, with a few exceptions (Perchoux et al., 2013). For instance, Leal and Chaix (2011) found that 90% of the studies examining the associations between built environment and cardiometabolic risk factors focused their analysis solely on residential environments. Perchoux et al. (2019) argue that the temporal aspects such as time spent at specific locations are only rarely considered. However, these concepts are increasingly relevant when data sources, such as smartphone location data, increasingly capture both high frequency spatial and temporal data. Detailed spatiotemporal data for individuals allow researchers to more fully understand the influence of environment, or more broadly of place, on individual health outcomes and health behaviours (Hobbs & Atlas, 2019).

1.2 | The exposome

The exposome is defined as the totality of human environmental exposures, in other words, all those exposures that are non-genetic (Hughes, 2014; Rappaport, 2011; Wild, 2005, 2012). It could be argued that the research on the exposome necessitates a geographical perspective (Jacquez et al., 2015) given the environment-person connections and movement of people between discrete environments. The quantification of such an all-encompassing concept is truly challenging at a single location in time, and even more complex over time. The long-term aim of this type of research would be to attempt to capture the totality of influences (spatio-temporally) on health and well-being over the life course. In this paper, we use an empirical case study as a point of departure to highlight the need for 'dynamic' conceptualisation by explicitly comparing with 'static' conceptualisations and to illuminate key challenges.

1.3 | Towards a dynamic conceptualisation of place

The static approache relates to the effects of place by utilising a single location, such as a house, workplace or school (Laatikainen et al., 2018). However, it is known that this does not accurately reflect the daily mobility of individuals *between* places (Thornton et al., 2017). Real time mobile location and GPS derived data are becoming increasingly ubiquitous. This data deluge, to some extent aids geographers desiring a 'dynamic' conceptualisation of place (Laatikainen et al., 2018) by utilising richer fine-grained data sources. Arguably, this dynamic conceptualisation allows for more precise place-based (or environmental exposure) estimates linked to daily movements. These new(er) data sources provide a more 'dynamic' assessment of the spatio-temporal effects of place on the health of individuals.

Emerging technologies also enable the potential for more rapid spatio-temporal intervention(s): avoiding areas of momentarily extreme poor air quality or 'nudges' away from or towards aspects of the environment such as alcohol outlets or greenspaces. The 'dynamic' work has only just begun, primarily using small sample populations (Apparicio et al., 2016; Donaire-Gonzalez et al., 2016; Oliver et al., 2015). However, it is becoming apparent that the use of personal location data is necessitating a shift in thinking in health geography research. The use of location has been integral in the endeavours of health or medical geography. However, there is emerging evidence that other fields, for example in mHealth (Donaire-Gonzalez et al., 2016; Steinhubl et al., 2015) or health research more broadly (Richardson et al., 2013) are discovering and promoting the value of spatial information. As others note, it is transportation and health that account for many of the advances in this area (Birenboim & Shoval, 2016).

The possibility and utility of using 'dynamic' approaches is a frequent point of debate in the exposure assessment literature, where there has been a flurry of intellectual activity often collecting GPS data and linking this to environmental exposures such as air quality (Steinle et al., 2013). Research in obesity and physical activity, such as 'spatial energetics', also grapples with 'dynamic' approaches (James et al., 2016). Nonetheless, there are many challenges and considerations associated with dynamic data collection and subsequent analysis (Rosenberg, 2016b). A brief, but non-exhaustive series of considerations relate primarily to privacy, ethics and accuracy; as location data collected at minute by minute intervals can expose personal routines and sensitive places (e.g. workplaces or health visits), as well as introducing a methodological conundrum of what to do about missing data (Vogel et al., 2019).

Mobility and its resulting associations between environmental exposures and health behaviours or outcomes may also differ by individual characteristics or by groups within the population. For instance, differences by socioeconomic status or age are infrequently considered (Fuller & Stanley, 2019; Kim et al., 2019; Portegijs et al., 2017; Smith et al., 2019). Exposure to fast-food outlets often differs by socioeconomic status as these outlets more readily locate in more deprived areas (Black et al., 2014; Wiki et al., 2019). In one of the few large studies to explore differences by population sub-groups, mobility trajectories of older men and women were higher during young adulthood and declined in early adulthood through to older adulthood (Falkingham et al., 2016). It is therefore reasonable to suggest that the residential neighbourhood environment may play a more important role in shaping daily life: to a greater extent for individuals who remain closer to home, such as older adults with reduced mobility or those who live close to many facilities in city centres (Hobbs et al., 2019; Rabe & Taylor, 2009).

1.4 | Case study aims: spot the (dynamic) difference

We extend this traditional review by using a case study to elucidate some of the key challenges when collecting personal location data. We propose that by operationalising 'dynamic' approaches we can better understand any differences to static approaches. In other words, to what extent does having 'static', compared to 'dynamic' information about individuals, potentially change the associated or modelled geographical risks or benefits? The outcome of our case study will be a deeper understanding of how place affects health as well as the degree to which exposures could be altered and how, as people move around and are exposed to changing environments. Within our case study, we selected individuals as stylised examples of the difference between static and dynamic approaches, hypothesising that duration of and extent of mobility should be different for each of the individuals; an employee, a hospital patient with COPD and a university student. Specifically, we aim to:

1. Quantify the difference between 'static' and 'dynamic' exposure.
2. Examine the extent of differences in dynamic exposure by individual characteristics.
3. Discuss the myriad of challenges uncovered by operationalising a dynamic approach.

2 | LEARNING BY DOING: OPERATIONALISING THE METHODS

2.1 | Personal spatio-temporal location data: static versus dynamic

Personal location data was collected from a university student (age 18-25), who we assumed would be mobile, a working age employee (office job, age 30-40 years), who we also expected to be mobile, but at different times of the day and a patient with COPD, (age 50+ years) likely to be less mobile due to illness. We exclude specific identifying gender, socio-economic or ethnic information from this case study. Ethical approval was gained for the study through the local human ethics committee. Data was collected using an application on the participants' smartphone within the study area, principally including the locations (latitude and longitude) at regular intervals (timestamp), as well as a measure of accuracy (in metres). Data on a sample day, for all three individuals at fine spatio-temporal scales (i.e. daily, every 10 min, and every 200 meters) was then used to quantify the extent of the differences in estimated environmental exposure (air quality) between static and dynamic approaches. The environmental exposure data was linked (as seen in Figure 1) to the personal spatio-temporal location data. For the static estimated exposure, we have used the home location from each of the three individuals. The dynamic personal location data was a sample (to limit the risk of disclosure), which was then matched with air quality data measurements within the study area. Further, we included a stochastic element in the personal location data in order to further reduce the disclosure risk to individual participants.

2.2 | Data processing and analysis: data matters

Spatio-temporal personal location data aggregated into 10-min intervals was used as the dynamic location for each individual. Where location data was missing, we used a linear approach to assume the person was located between the points immediately preceding and after any missing data. The most common case of the missing points usually occurred when participants turned off their smartphones or GPS location while at home. In order to quantify the range of individual movement 'away' from home, we proposed a metric that reported the time spent more than 100 meters from the home address as 'away' from home. This allowed us to adjust for most of the inaccuracy in the GPS data collected and capture actual incidents of mobility linked to the potential differences in estimated exposure whilst preserving confidentiality. The location data (both static and dynamic) was then related back to estimated interpolated air quality surfaces at a fine spatio-temporal scale to extract actual concentration of air quality ($PM_{2.5}$) at every given location and time. This dynamic data was then compared with the static equivalent based on home address location of the individuals involved. Figure 2 shows an example of such linked dynamic location data and air quality ($PM_{2.5}$) levels. The locations in the example are simulated data and do not show any of individuals from the case study.

3 | LESSONS LEARNED: MOVING FORWARDS, BACKWARDS, AND SIDEWAYS

3.1 | Matters of time and space

Using a simplified and carefully curated case study allows the deeper investigation of important methodological considerations. Firstly, the spatio-temporal variation is shown in Table 1 highlighting variation in the amount of time spent at home or away (from home) for each individual. The time spent at home is therefore a static (place of residence) estimated exposure time. The time spent 'away' is analogous to the potential dynamic versus static misclassification. Note that time spent more than 100 meters from the home address is categorised 'away' from home. The time spent at home is highest for the patient at 920min (15h, 20min), followed by the student at 900min (15h) and then the employee at 630min (10 h, 30min). This means that the potential misclassification of environmental exposure is; 520, 540, 810min for the patient, student and employee respectively. For example, the student has a much lower level of estimated mean exposure from both static and dynamic, whereas the patient or employee have much higher exposures under either approach, peaking at around 90 and 100 respectively (Table 1). This meets our first and second methodological aims in understanding and quantifying potential differences between static and dynamic exposure.

3.2 | Differences by population characteristics: age and stage

Figure 3 visualises a daily dynamic approach to exposure, accounting for an individual's movement, reporting the estimated exposure, time and distance (meters) from the home address of each individual. Importantly, both distance from home (space) and duration (time) away from home affect exposure estimates. In the case of the

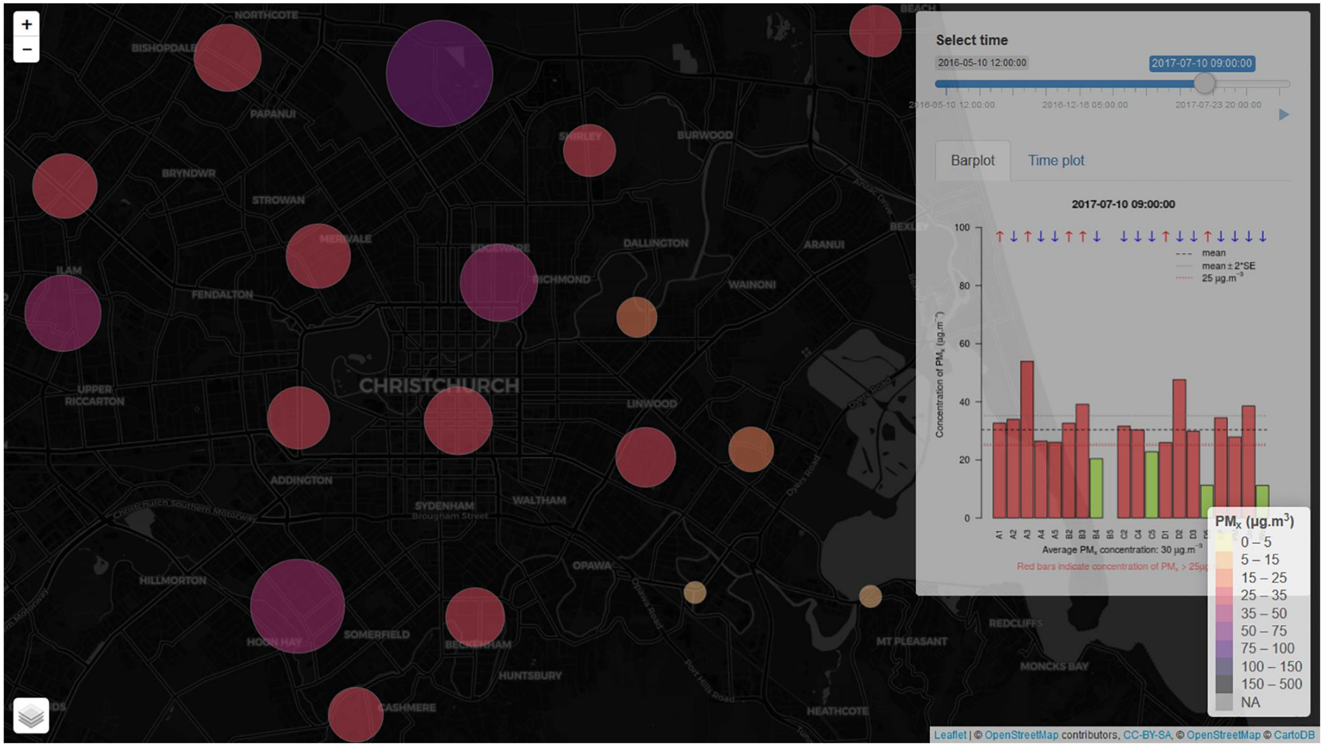

FIGURE 1 Christchurch CBD and location of air quality monitoring sensors (https://chchairquality.shinyapps.io/airquality/)

FIGURE 2 Example of linked dynamic location data and air quality ($PM_{2.5}$) levels. The location data is simulated. The interactive web map is available at chchairquality.shinyapps.io/PMexposure

TABLE 1 Estimated air quality exposure based on static and dynamic measures

	Time (min/24 h)		Estimated exposure ($PM_{2.5}$ in $\mu g.m^{-3}$)									
			Minimum		Maximum		Mean		Median		Daily sum	
Individual	Home	Away	Stat	Dyn	Stat	Dyn	Stat	Dyn	Stat	Dyn	Stat	Dyn
Employee	630	810	2.8	2.8	102.9	102.9	38.9	27.9	29.9	14.8	5570.1	4020.4
Patient	920	520	3.6	4.0	91.7	91.7	41.0	40.0	47.0	34.6	5903.5	5767.9
Student	900	540	4.1	4.1	36.8	41.1	13.9	14.2	11.1	11.2	2004.2	2054.1

student, proximity to the home address, on the vertical axis (Figure 3), appears to be accounting for the smaller differences between static and dynamic estimates (see Figure 4). For the patient, the distance away from home is greater, but the time away from home (static) is also slightly shorter, limiting the misclassification. However, for the employee, both the longer period (time) and distance (space) away from home combine to give the much larger differences in (spatio-temporal) estimated exposure between the static and dynamic approaches. What we can observe and reflect on is that there can be higher values either when individuals pass through (dynamic) or reside (static) in areas of high exposure. Figure 4 visualises the differences in values of 'static' versus the 'dynamic' estimated air quality by individual, in other words the potential misclassification of environmental exposure, where the bars represent the absolute differences in estimated exposure between the static and dynamic. The largest differences in air quality exposure between 'static' and 'dynamic' appear for the employee (Mean: 38.9 $\mu g.m^{-3}$ vs. 27.9 $\mu g.m^{-3}$; Median: 29.9 $\mu g.m^{-3}$ vs. 14.8 $\mu g.m^{-3}$) with wide ranging minimum and maximum values (2.8 and 102.9 $\mu g.m^{-3}$). The employee has a distance range of just over 5 km from the home location (Figure 3). The patient has similar mean exposure values of *'static'* and *'dynamic'* (41.0 $\mu g.m^{-3}$ vs. 40.0 $\mu g.m^{-3}$) and also minimum and maximum (3.6 $\mu g.m^{-3}$ vs. 4.0 $\mu g.m^{-3}$; 91.7 $\mu g.m^{-3}$ vs. 91.7 $\mu g.m^{-3}$), but a notable divergence in median value (47.0 $\mu g.m^{-3}$ vs. 34.6 $\mu g.m^{-3}$). Finally, the student spends a similar amount of time at home as the patient (and considerably more than employee). However, they do not travel as far as the others (2.5 km, see Figure 3). The corresponding minimum (4.1 $\mu g.m^{-3}$), maximum (36.8 $\mu g.m^{-3}$ vs. 41.1 $\mu g.m^{-3}$), mean (13.9 $\mu g.m^{-3}$ vs. 14.2 $\mu g.m^{-3}$) and median (11.1 $\mu g.m^{-3}$ vs. 11.2 $\mu g.m^{-3}$) values of estimated exposure are similar, but much lower than for the patient, suggesting residence in a lower pollution area.

The estimated patterns of static exposures suggest movement from higher to lower exposure areas for the patient and employee, and movement into higher exposure areas for the student. Overall, the differences between static and dynamic exposure of the patient and student are not large, but the variations in employee's daily movement are prominent, with the median exposure for the dynamic estimate (14.8 $\mu g.m^{-3}$) being only half of the size of the static estimate (29.9 $\mu g.m^{-3}$). It would be fair to conclude that mobility alters the potential exposure, markedly so as the distance and time away from home increases. In other words, 'dynamic' (non-residential) exposure and mobility are closely linked.

4 | DISCUSSION

4.1 | Statement of principal findings

This article has critically examined progress in the conceptualisation of location in health-related geospatial research and demonstrates how the static and dynamic approach to the utilisation of location may affect results of individual exposure estimates. Our exploratory case study demonstrates how daily mobility varies beyond static definitions of neighbourhood and home location and the implications for health geography. Secondly, we highlight

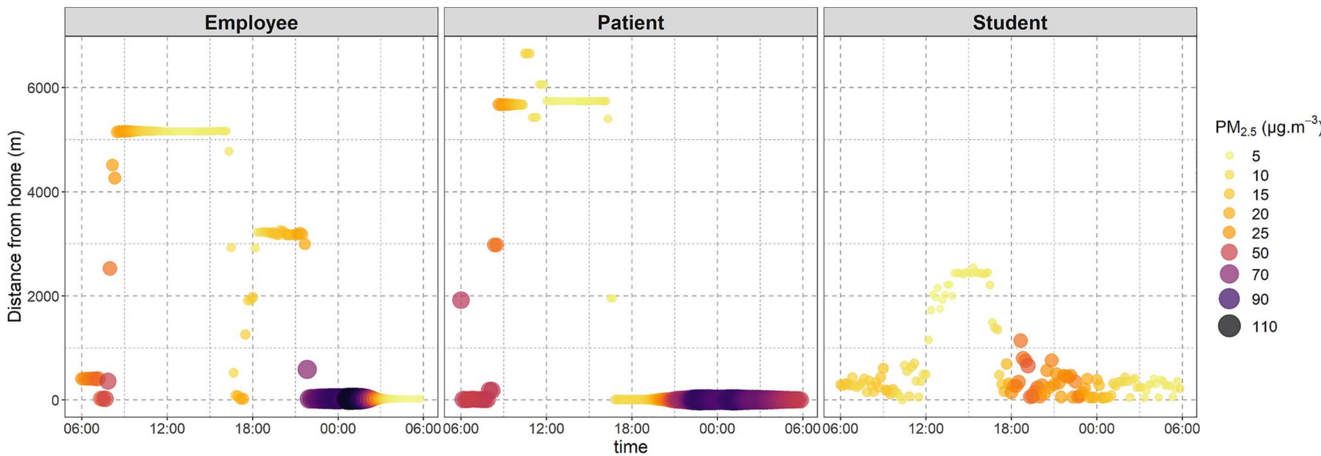

FIGURE 3 Dynamic environmental exposure, time of the day (horizontal axis) and distance from home (vertical axis)

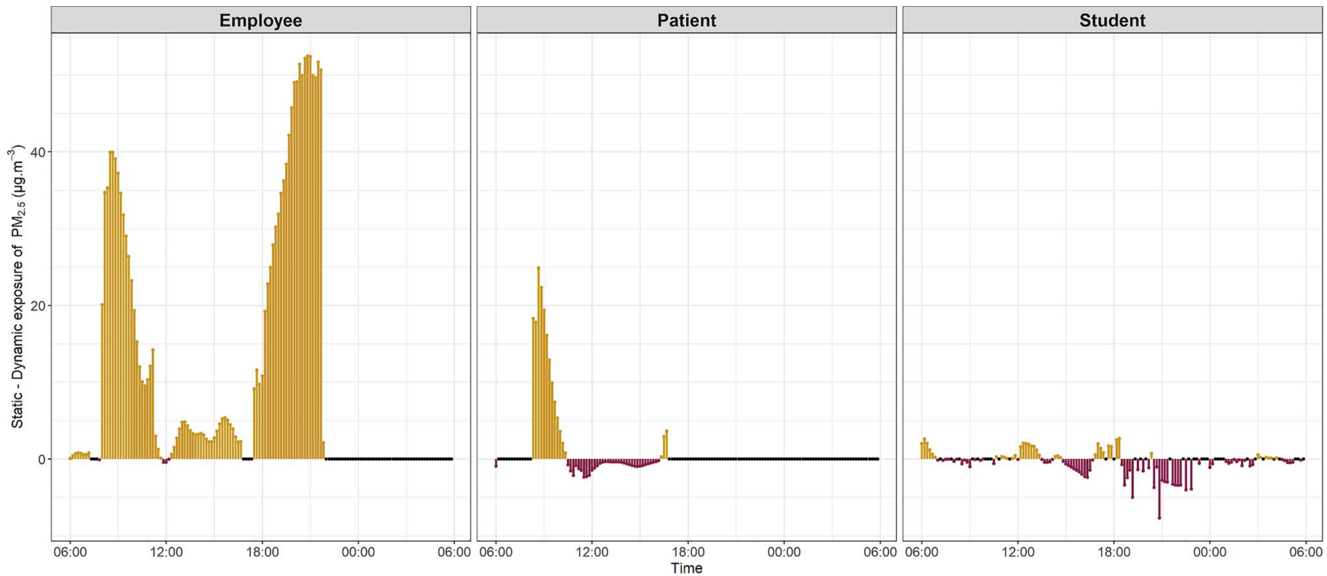

FIGURE 4 Static minus dynamic exposure with the three panels quantifying misclassification by participant (more than zero = over exposure; less than zero = under exposure; zero = no exposure difference static minus dynamic)

that the differences between static and dynamic conceptualisations also affect the estimates of individual exposure to poor air quality. In our case study, poor air quality is highest in the evening: this is salient as it also means that the static (residence based) estimated exposures are likely at their highest when the individuals are at home in the evening. Further, we show the importance of assessing exposure for different individuals (or groups) in the population, particularly those whose mobility either is a significant part of daily activity or conversely, is not. Spatio-temporal movements (mobility patterns) have critical differences on the estimated exposures.

4.2 | Study meaning and other evidence

It could be argued that there is a significant degree of potential misclassification of environmental exposure for some individuals; for example, those with the highest *duration* of mobility. A weekly variation of between 10–14 h a day of temporal misclassification would mean 152–213 missing days of the year on an annual basis. Using basic assumptions about movement patterns, this could be considered the equivalent of losing half of all data. We need to make an accurate assessment of if, or how, the environment could be altering individual health outcomes. This supports previous evidence from Britain which suggested that mobility trajectories change over time and by person (Falkingham et al., 2016).

Our study has allowed us to build on previous research in health geography and that elucidates the impact of area, or place, on health outcomes and behaviour. The 'dynamic' work has really only begun and mostly on small study samples (Apparicio et al., 2016; Donaire-Gonzalez et al., 2016; Oliver et al., 2015). We have explored some of the possibilities described by Birenboim and Shoval (2016) when discussing smartphone data, "these devices represent a boon to researchers, giving them the opportunity to collect continuous and intensive high resolution data in time (seconds) and space (meters) for long periods of time – something that has never before been possible in geographic or social science" (p. 283) by collecting this data, albeit not at quite the intensive frequency envisaged. We would argue that the statement above is correct, and it does provide many opportunities for the researcher, but perhaps we have not yet fully grasped, nor serendipitously stumbled across, all the additional limitations and challenges created by use of this new data source (Laatikainen et al., 2018; Vogel et al., 2019).

Our study addresses an earlier concern of Inagami et al (2007) about the lack of studies that "examined the contextual influence of an individual's "activity space" on health outcomes" (p. 1780) by collecting data that allows us to determine the extent of movement. By following individuals daily, we also can better understand what the appropriate context may be. This study also relates to UGCoP (Kwan, 2012) by showing what this appropriate context may be, albeit on a smaller sample of individuals and showing that who those individuals are matters also. Indeed, as Kwan (2009) argues, "people-based measures would provide much more accurate representations of the contextual determinants of health behaviours and outcomes" (p. 1313) we find this to be the case and have shown that the UGCoP is a key consideration in health research with a spatial aspect.

Moreover, our case study supports other evidence specific to air quality (Setton et al., 2010) which found that bias changes as mobility increases away from residential location, but the effect depends on whether an individual is mobile from, or into, a pollution 'hot-spot'. We also find that mobility does alter the potential exposure, in both the range of mobility and its duration. Furthermore, as Dewulf et al. (2016) report no studies have used mobile phone data to dynamically estimate the exposure to air quality as we have done here. However, a key challenge remains in using more data, "for an entire week, month or even year" which is preferable (Dewulf et al., 2016). The future 'holy grail' should include a significant sample size over a period, (e.g. over a lifetime), a non-trivial task given the resource needed. Moreover, Steinle et al. (2013) allude that personal exposure assessment requires the recording of a time-activity patterns for every individual concomitantly with pollutant concentrations in the environment. We have tested the claim, to a degree, of Spielman and Yoo (2009) that cell phone tracking may help solve the problem of appropriate 'frame' and the extent of the effect on individual variability on a daily basis and how it could plausibly influence research findings, coefficients and model fit statistics. We would also argue that we have addressed a concern of (Rosenberg, 2016b) to "re-assess our old ideas, seek new ideas and avoid the traps of new determinisms" (p. 8) by using a fresh approach to better understand how this could be occurring in the specific case of environmental determinisms.

It is clear that a dynamic conceptualisation of environment is important, but, it is also a resource intensive exercise to gather this data. Although we can 'solve' the problem on smaller samples, a whole of population assessment will take an extraordinary scale of research endeavour. Thus, we would concede that an emphasis on those groups we think have distinct mobility patterns should be a focus in the first instance. (Jacquez, Sabel, & Shi, 2015) have called for a Genetic GIScience, which connects not only the Exposome, but the Genome (human biology) and the Behavome (social, societal and behavioural determinants combined). Our exploratory study here offers a small but significant glimpse into the grandiose nature of attempting to measure not just a single environmental variable, but the totality of everyone's exposures. Our results are different from (Lewin, 1951) who argued that "most of daily life takes place at different places outside the home" (p.130), we extend longstanding evidence and add the caveat that this is perhaps true for the healthier proportion of the population. Nevertheless, we don't find this to be the case for everyone, for example, the patient and perhaps more surprisingly, the student. We are therefore in broad agreement with (Inagami et al., 2007) in that, "the geography of individual's activity over time, is not limited to the residential neighbourhood" (p. 1780), with the exception of the student.

4.3 | Strengths, limitations, and considerations

The findings of our review and case study should be interpreted considering our study limitations and strengths. First, our review is not systematic and therefore may have excluded some sources. Second, the main issues with such personal location data stem from a lack of a clear set of standards for reproducibility, of which the authors are aware. It is not appropriate to share the raw data from this study. However, we have remedied this as far as possible by describing the method and using visualisations to aid the reader. We also do not, at this stage, take into account the mode of travel, whether car, bus, train, bicycle or on foot as others (Apparicio et al., 2016) have managed on small samples ($n = 10$). Students are potentially likely to travel smaller distances, on foot, more often, given the low level of car ownership but are proximate to a variety of destinations in the study area. We also cannot determine what activity the individual is engaged in at the specific location, for example, whether working in an office, purchasing alcohol, exercising in green space and so forth. We could also infer the mode of travel or activity from the location, for example working at the office: something that should be pursued in future studies, to add a richer context.

It is worth noting we used the estimated exposure to air quality, this is a challenge dynamic observation studies face. We therefore simplified the statistics and sums of exposure to mean concentrations for a given time and place. Further, since we were not able to determine if an individual was indoors or outdoors, $PM_{2.5}$ exposures are still denoted as estimated. To fully understand the complete picture of exposure to poor air quality, or indeed the all-encompassing exposome, we still need to know much more than is currently possible to collect from an individual both indoors and outside as well as a host of other factors without considering the problem of missing data. There are also some errors in GPS accuracy manifest in the personal location data. We acknowledge this, as have many others, but would ask the reader to consider that the degree of error, say 50-100 meters, is much less important in the context of the wider misclassification error. However, these are persistent limitations that challenge the field. Indeed, as a recent review also articulates (Smith et al., 2019), much of the research in the area of environmental exposure assessment or studies using personal location data is rather applied in nature. Further, it is still grappling with reasonably fundamental questions of the appropriate sampling rates, study durations or methodologies, as well as questions of data accuracy or quality (Laatikainen et al., 2018).

4.4 | Future research and unanswered questions

We see applicability of the dynamic approach to a wider set of specific areas of health geography that are likely to benefit such as; other environmental exposures (air quality, greenspace or bluespace), proximity to alcohol (Geiger & MacKerron, 2016), tobacco or smoking cessation (Schick et al., 2018), food outlets (Kestens et al., 2010), or health services: to name a few more directly applicable where area based (static) measures of exposure are often used. Indeed, as Helbich (2018) notes, “there is ample need for dynamic exposure conceptualisations in mental health research” (p. 132). There are also moves towards using geo-social data (e.g. Twitter) to identify and or track mobile populations over time with respect to their exposure context (Gruebner et al., 2017) and its potential mental health implications. Other uses of the approach presented here would be to validate or assess the extent to which simulation models align with the real GPS data from smartphones (Sallah et al., 2017). Our next step is to expand the size of the cohorts we track over time to see the degree to which these initial findings presented here apply to a wider range of the population (Campbell, Marek, et al., 2021). It is fair to say that much research in this area is in its infancy.

A significant challenge of using personal location data remains the privacy concerns given the highly identifiable data, for example home address (Jacquez, Essex, et al., 2017; Richardson et al., 2015). These considerations are also particularly relevant here and the subsequent implications for reproducibility and transparency of data. There is also a real challenge around the consistency of data analysis methods for personal location data, especially in dealing with missing information (Buliung & Kanaroglou, 2006; Newsome et al., 1998). With this in mind, we adopt a cautious approach to the full disclosure of all steps taken to minimise these risks, whilst balancing the opportunity to replicate the methods of this study. We would argue that it is not possible to exactly replicate the study dataset given it occurred for a place and time period and so explain the principles and procedures followed to allow as transferable or replicable an approach as possible. This of course evokes consideration of the Modifiable Temporal Unit Problem (Cheng & Adepeju, 2014). We aggregate data to ten-minute measurements, understanding that this loses some of the accuracy of the data and introduces a potential inferential bias. However, this provides the framework for the straightforward linking of environmental and location data, whilst allowing the retention of the dynamic nature of the data. We are intentionally not disclosing the specific dates and times of the personal location data collection in order to further remove potential disclosure risks. A key challenge is to balance the need for scientific reproducibly with privacy and ethical considerations.

A key question remains for us as (Birenboim & Shoval, 2016) articulate, “do people, once they know they are being followed, change their activity? If so, how?” (p. 289), in other words, does the Hawthorne effect apply? This represents a potential issue for the researcher, as attempting to address such a question would require potential deceit or perhaps the use of a ‘placebo’ smartphone application. The other challenge in collecting such data is that it is resource intensive and requires willing participants, with a perception that this is a non-trivial task to undertake. As others report (Brusilovskiy et al., 2016) on small samples (n = 5), “none of the five participants expressed any concerns about having their location tracked” and further were “very interested in looking at the maps that showed their mobility” (p. 141). This also presents a conundrum however; as the scale increases, a problem emerges which appears to suggest the opposite. As reported in a large scale asthma study that collected geolocation alongside other variables (Chan et al., 2017) with over 40,000 downloads of a mobile application that collected data from only 2317 ‘Robust Users’. This suggests personal connection is important, making large scale attempts to collect such data problematic. Other research shows iPhone users have higher education levels and income compared with other smartphone users and smartphone users more broadly have higher income and education than the population, according to American research (Pew Research Center, 2015), highlighting potential bias and inequity in personal location data samples. Mobile phone data, whilst useful in providing a new avenue for exploration, is also not bereft of issues in itself. As such, one much carefully consider the issues of who owns the data, governance, as well as carefully considering who is absent (the digital divide) from the data collected.

5 | CONCLUSION

In summary, this paper points to an important moment for health geographers to engage in the utilisation of personal spatio-temporal location data in our research endeavours. We demonstrated that on a daily basis there are twofold differences in individual environmental exposures between a static and a dynamic approach. Perhaps, the magnitude of error is more fully appreciated if we were to argue that this is akin to assigning erroneous demographic and socio-economic data to between a quarter and one half of all people in a national Census. This would have important consequences for understanding patterns and future analysis on the data. This should provoke a more serious engagement with sources of dynamic data that could address such a salient issue. These results have important implications for health geography when attempting to quantify the role of place(s) on individual or population health by altering any inferences made. Conducting the 'static' and 'dynamic' approaches in parallel enables deeper understanding of the differences of each conceptualisation: more fully understanding potential inferential discrepancies and gaining insights into what accurate representations of the places people spend time (their true context) may be. Indeed, it is now imperative that health geographers engage in endeavours that attempt to address potential bias in research including environmental exposures by using dynamic conceptualisations of place. While this is challenging, we conclude by arguing that it is critical, indeed vital, that health geography, with a rich traditional history of incorporating location data, is central in developing the methods and theoretical framework for such future research endeavours.

ACKNOWLEDGMENTS

Thanks to the participants of the studies that provided data for the empirical case study.

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How to cite this article: Campbell M, Marek L, Hobbs M. Reconsidering movement and exposure: Towards a more dynamic health geography. *Geography Compass*. 2021;1–17. https://doi.org/10.1111/gec3.12566