

This article was downloaded by: 10.3.97.143

On: 01 Apr 2023

Access details: *subscription number*

Publisher: *Routledge*

Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: 5 Howick Place, London SW1P 1WG, UK



Routledge Handbook of Health Geography

Valorie A. Crooks, Gavin J. Andrews, Jamie Pearce

Spatial modeling's place in health geography

Publication details

<https://www.routledgehandbooks.com/doi/10.4324/9781315104584-48>

Sara McLafferty, Sandy Wong

Published online on: 11 Jun 2018

How to cite :- Sara McLafferty, Sandy Wong. 11 Jun 2018, *Spatial modeling's place in health geography from:* Routledge Handbook of Health Geography Routledge

Accessed on: 01 Apr 2023

<https://www.routledgehandbooks.com/doi/10.4324/9781315104584-48>

PLEASE SCROLL DOWN FOR DOCUMENT

Full terms and conditions of use: <https://www.routledgehandbooks.com/legal-notices/terms>

This Document PDF may be used for research, teaching and private study purposes. Any substantial or systematic reproductions, re-distribution, re-selling, loan or sub-licensing, systematic supply or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The publisher shall not be liable for an loss, actions, claims, proceedings, demand or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

SPATIAL MODELING'S PLACE IN HEALTH GEOGRAPHY

Trends, critiques and future directions

Sara McLafferty and Sandy Wong

Spatial modeling comprises a set of methods and approaches for measuring, analyzing and visualizing geographical relationships among people and the contexts in which they live, work and interact. For centuries, these methods have been central to health geographers' efforts to understand and improve population health and well-being and access to health services. The methods emphasize spatial relationships – those based on location, distance and proximity – as critical dimensions of health and health care. Looking back, the history of spatial modeling in health geography reveals both enthusiastic adoption of the methods and trenchant critiques of their validity and value. The give-and-take between embrace and critique led to the current pluralistic state in which spatial modeling stands alongside other methodologies as a well-used approach in health geography and a vibrant area of research endeavor. Spatial modeling has also achieved considerable success and impact as an arena for cross-fertilization with disciplines such as epidemiology, biostatistics and diverse health-related fields.

This chapter begins by discussing the historical and intellectual trajectory of spatial approaches in health and medical geography, focusing on key questions, debates and realignments. Later sections discuss current spatial methods and themes, along with ongoing critical directions and topics for future research.

Historical and intellectual trajectory

Much early work in medical geography relied on spatial association, the most basic form of spatial modeling. John Snow's map of cholera cases in the London epidemic of 1854 suggested clustering patterns and spatial associations with water pumps that offered clues about disease etiology. Jacques May's treatise on medical geography (May, 1950) provides many examples of using spatial association to shed light on geographical determinants of disease. In fact, his key insight – that disease agent, host and vector must coexist in space and time for disease transmission to occur – is based on spatial associational reasoning.

Building on these early works, the 1960s and 1970s saw the rapid adoption of quantitative methods of spatial analysis. Following the quantitative revolution that was sweeping geography at the time, many medical geographers embraced multivariate statistical methods in analyzing spatial associations between disease incidence and environmental factors. These methods were analogous to the visual and ad-hoc approaches adopted by earlier researchers, but their use of complex algorithms and hypothesis-testing procedures gave them an aura of scientific rigor and validity. Other researchers moved beyond spatial association. Peter Haggett and Andrew Cliff (in the United Kingdom), and Gerald Pyle (in the United States) developed

dynamic models of disease diffusion that included both spatial and temporal elements. Research on health services adopted methods such as location-allocation modeling to identify optimal service locations and gravity modeling to analyze potential access to health services (Knox, 1978). These approaches advanced the field by explicitly modeling spatial relationships based on proximity, location and distance. Gesler (1986) offers a thoughtful summary of medical geographers' adoption of spatial-analytic methods in the 1960s and 1970s.

Debates and critiques

Important critiques of spatial analysis emerged in the 1980s and early 1990s as social-theory and political-economy perspectives gained prominence in medical geography and as emerging health concerns raised questions about traditional approaches. The HIV/AIDS pandemic revealed the complex politics of infectious disease, its uneven spread and the inadequate public-health response. Moreover, widening health inequalities in the 1980s and 1990s in many economically developed countries showed that people's health was driven by much more than environment and location.

Spatial modeling, and the quantitative methods on which it is based, were key targets in those critiques. Debates about the role of spatial modeling in medical geography focused on four main themes: First, spatial methods were criticized on epistemological grounds, for their inability to establish *causation* from evidence of spatial association. In discussing spatial analysis of disease, Mayer (1983) described the ambiguous relationship between spatial patterns of disease and the underlying processes that generate those patterns: spatial patterns reflect complex and multiple causal pathways that may not be evident in ecological associations. Mayer also raised a series of important conceptual challenges, including the lack of attention to the roles of emotions, experiences and social networks in disease etiology and varying cultural conceptions of disease. Second, spatial methods were criticized for their failure to shed light on the political-economic processes that shape relationships between places and health. According to Mohan (1989), many spatial studies adopted a position of "technical neutrality" (p. 169) devoid of consideration for the political and social forces that impact health and health-care inequalities. Spatial methods' failure to illuminate key health issues at that time, including health services privatization, HIV/AIDS and increasing disparities in population health, revealed the methods' inherent political-economic limitations.

The third area of critique focused on the inability of spatial models to reveal people's experiences, perceptions and agency (Dyck, 1999). People were often modeled as faceless and interchangeable entities. Characterized as "genderless and colourblind" (Pearson, 1989, p. 9), medical geography's spatial-analytic focus neglected key axes of social difference. Although this omission is not inherent to spatial methods, it represented the nature of most spatial-analytic research by medical geographers at the time. Pulling these themes together, the fourth critique centered on spatial methods' emphasis on space as opposed to place. By definition, spatial methods are concerned with space – location, proximity, distance and so on. Space is treated as a container in which events unfold, ignoring the recursive relationships between people and places. Kearns' (1993) described the spatial perspective as a *placeless* endeavor that fails to consider how people's health and well-being relates to their place-based experiences and active agency in place-making.

The emphasis on place in contrast to space significantly changed the course of medical geography and led to its newfound focus on health and place and the growing use of qualitative methods. Although qualitative methods were used earlier by researchers like Jenny Cornwell and John Eyles, and field-based research was always a mainstay in medical geography, qualitative methods gained great prominence in the 1990s, as evidenced by a special issue of the *Professional Geographer* devoted to qualitative methods in health geography (Dyck, 1999). The journal *Health & Place* was introduced to foster and represent this important shift from medical to health geography and from quantitative spatial analysis to qualitative and mixed methods.

Spatial modeling in the 1990s and 2000s

Despite these critiques, the spatial analysis and modeling tradition endured. Technological developments in computing and data storage greatly increased geographers' ability to analyze large geospatial datasets, and geographic information systems (GIS) for analyzing these datasets became ubiquitous. Medical/health geographers harnessed these developments to facilitate the kinds of spatial, locational and spatiotemporal analyses that were first proposed in the 1970s. Technological developments also enabled much more complex and computationally intensive types of spatial analysis. Multilevel modeling, in which health outcomes are modeled as functions of environmental and social factors at multiple spatial scales, gained a strong foothold among health geographers (Duncan, Jones and Moon, 1998). Health geographers developed and introduced important spatial epidemiological methods, such as methods for visualizing complex disease patterns and detecting disease clusters (Gatrell et al., 1996). At the same time, GIS emerged as a crucial tool for integrating, visualizing and analyzing large geospatial datasets on social and environmental factors and health outcomes (Cromley and McLafferty, 2002). A review by Rosenberg (1998) identifies the many developments in spatial-analytic perspectives in health geography in the 1990s.

The growth of spatial modeling in the 1990s and early 2000s was also closely tied to health geographers' involvement in multidisciplinary research teams. Health geographers' spatial-analytic skills were in demand as biomedical and public-health researchers began to explore socioecological and environmental influences on health. In Canada, the United Kingdom and the United States, health geographers spearheaded and participated in large, funded research projects addressing a wide range of health and health-care issues. In the 1990s in the United States, the Centers for Disease Control sponsored conferences on GIS and health, and agencies like the National Cancer Institute organized working groups and panels that addressed geospatial perspectives. These and other funded research endeavors contributed greatly to the field's expansion and innovation.

Thus, by the end of the millennium, a strong pluralistic model had emerged in health geography, in which both quantitative and qualitative research methods held prominence. Both sets of methods coexisted and thrived, each with a strong set of advocates. In addition, some prominent health geographers – Graham Moon, Susan Elliott, Mark Rosenberg, Sarah Curtis and many others – bridged both worlds. There was broad recognition that each set of methods could provide useful insights in particular research contexts. As Elliott (1999, p. 240) wrote: "And the question shall determine the method." Health geographers also advocated for mixed methods that combined the population-level insights derived from quantitative methods with the detailed process-based knowledge gained from qualitative methods. These mixed methods are widely used in contemporary health-geographic research.

Current trends

Several broad areas of research and application that leverage advances in web and mobile technologies and computing power are at the forefront of contemporary work on spatial modeling in health geography.

Space-time and longitudinal analysis

Researchers have long recognized that the processes impacting health and health care unfold in space and time, but the complexity and computing power needed to handle space-time data posed major barriers to spatiotemporal analysis. As these barriers have fallen, health geographers have developed and implemented novel methods for dynamic and space-time analysis. Some of these methods represent straightforward extensions of existing spatial methods, such as kernel density estimation, spatial autocorrelation analysis and spatial cluster detection, to include time as an added dimension. Clusters of health events in both space and time can be identified to provide clues about disease etiology and information for policy-making and intervention.

Cluster-detection methods that incorporate longitudinal data on residential histories, historical environmental exposures and disease latency periods have also been developed (Sabel et al., 2009).

Use of longitudinal methods is increasing in health geography. These methods represent the dynamic associations among variables over time, enabling analysis of complex relationships between people and places. Places change via economic, social and environmental processes, while people's behaviors, interactions and experiences both shape and are shaped by place change. Longitudinal methods that capture this dynamism have provided important evidence about the effects of migration on health and health inequalities. Longitudinal research in Scotland shows that healthy young people often move out of deprived areas to less-deprived, and generally healthier, areas (Norman, Boyle and Rees, 2005). These selective migration processes exacerbate health inequalities as flows of healthy out-migrants from deprived areas diminish health status in the places they leave and enhance it in the places they move to.

Efforts are underway to model and simulate the health-related behaviors of individuals over space and time. Geographical research using *agent-based models* is greatly expanding as the models are employed to simulate space-time patterns of disease spread based on data describing people's mobility patterns and spatial interactions, as well as characteristics of the social, built and natural environments (Mao, 2014). Results of these models are useful for predicting where and how quickly emerging disease outbreaks might spread. A related class of methods involves *spatial microsimulation*, a process of simulating population-level trends and patterns. Health geographers have implemented both dynamic and static versions of these models to provide small-area estimates of health-related behaviors and to analyze changes in health inequalities over time (Smith, Pearce and Harland, 2011).

Multilevel modeling

Multilevel modeling is increasingly used in health research, accelerated by computational advancements and software developments in the last three decades. By considering interactions between people and contexts, multilevel models avoid individualistic and ecological fallacies that limit other statistical methods (Owen, Harris and Jones, 2016). Health geographers were early adopters of multilevel modeling and have used it extensively to investigate social and contextual determinants of health (Duncan, Jones and Moon, 1998).

To account for multiple and overlapping spatial contexts that influence individual health outcomes, researchers have included two or more contextual effects in hierarchical models and used cross-classified models in which the contextual effects are not hierarchical. In one case of a four-level model, individuals were nested in households nested in communities nested in regions to examine the effect of income inequality on self-rated health (Subramanian et al., 2003). A study on childhood obesity used a cross-classified structure in which individuals were nested in both residential areas and schools (Townsend, Rutter, and Foster, 2012).

Multilevel models emphasize scalar relationships, but their treatment of space has tended to be naïve. *Spatial autocorrelation* can persist in multilevel models even after accounting for individual and contextual effects. Recent contributions tackle this issue by modeling spatial relationships among contextual units along with contextual effects (Arcaya et al., 2012). Results reveal clustering of health outcomes that emerges from spatial processes and interactions that cut across area boundaries. Other recent developments include *multiple membership models*, in which individuals are assigned to several neighborhood-level units simultaneously. These models acknowledge the important fact that people's health is affected by the many contexts they experience throughout their daily lives.

To model changes in contextual effects over time, there are emerging developments at the intersection of multilevel modeling and life-course epidemiology. A life-course perspective enriches our understandings on the relations between health and place by identifying critical time periods for and cumulative effects on health outcomes as people age. Næss and Leyland (2010) used a correlated cross-classified model, with data

from four cohorts at four time points, to identify residential locations for people at particular life stages that most strongly affect their mortality risk.

Modeling of activities and exposures

To better understand contextual dimensions of health inequalities, opportunities, behaviors and risks, scholars are increasingly turning to spatial techniques to model individuals' health-related activities and exposures. This broad and diverse field increasingly relies on Global Positioning System (GPS)-based tracking devices and environmental sensors to track people's movements through space and time and record their exposures to changing environmental conditions.

Activity spaces are the physical spaces that people travel through and have access to over the course of daily activities. To move beyond the use of static residential units as proxies for context, activity spaces are utilized to capture multiple, non-residential and more accurate environmental influences on health outcomes over space and time (Kwan, 2012; Perchoux et al., 2013). Popular activity-space applications include the standard deviational ellipse, network buffer, kernel-density estimation and potential path area, which are typically used to identify the locations, sizes and features of activity spaces. Activity-space size has been found to be significantly correlated with diverse health-related issues, including health-care opportunities, dietary behaviors and risk of depression. Usually the larger the activity space, the better the health outcome and geographic access to health-promoting opportunities. Increasingly, researchers use GPS devices to record highly detailed space-time activity patterns associated with health outcomes and exposures (Zenk et al., 2011).

Using GPS-based activity tracking raises thorny methodological and conceptual issues. Detailed location data are often unavailable due to privacy and confidentiality restrictions. Tracking devices generate enormous streams of data, with varying, and occasionally unknown, levels of accuracy and precision, and complex algorithms are required to generate meaningful information. Most importantly, the fact that space-time activity spaces result from individual decision-making processes creates ambiguities in analyzing their role as health determinants. People actively choose spatial contexts, so an observed contextual effect on health may reflect preferences and choice rather than context, resulting in *selection bias* (Chaix et al., 2013). Although statistical methods exist for evaluating selection bias, their application to real-time tracking data that reflect mundane, everyday decisions is poorly understood.

Similar trends are underway in research on monitoring and measuring environmental exposures. Spatial patterns of air pollution have been estimated using universal kriging (Jerrett et al., 2001) and land-use regression models. In recent years, geographers have moved away from these traditional static models to more dynamic ones that are sensitive to space-time variations in individual mobility and air-pollution concentrations. Lu and Fang (2015) estimated personal exposure to both ambient and indoor air pollutants using space-time trajectories to identify danger zones where the health impact from air pollution was highest. Improvements in exposure assessment have been facilitated by technological advancements in personal environmental monitors and remote sensing (Steinle et al., 2015).

Spatial-accessibility modeling

Spatial-accessibility models estimate the local availability, supply and proximity of health-related services to populations in need. Although early applications of the models focused on health-care services, recent applications encompass parks and recreation facilities, food outlets, social services, risky spaces and other places that impact health and well-being. The simplest models include *container* measures that describe the ratio of services to population within fixed geographic zones and distance measures that determine Euclidean or network distance to the closest service facility; however, these have well-known limitations (Higgs, 2006). Also, widely used are gravity and potential models, which have been extended to incorporate factors, such

as access to transportation, that restrict spatial access for vulnerable, low-income and elderly populations (Lovett et al., 2002).

Much recent research centers on *floating catchment area* (FCA) models, which determine geographically varying service-to-population ratios within overlapping spatial windows (Luo and Wang, 2003). The original two-step FCA (2SFCA) method involved determining the provider-to-population ratio within a catchment of each service provider and then summing the ratios within the catchment of each population zone. Researchers have made many enhancements to the 2SFCA, including incorporating distance decay effects, alternative transportation modes, variations in catchment sizes and differences in population health needs (Wang, 2012).

Researchers are also considering the role of time, as well as space, in service availability and access. Hours of operation for service providers and temporal variation in the types of services offered intersect with people's space-time constraints and daily activity patterns to restrict access (Widener and Shannon, 2014). Used in analyzing access to food stores, novel spatiotemporal accessibility measures integrate data on typical movement patterns throughout the workday with store opening and closing times (Widener et al., 2015).

These and other recent developments bring spatial-accessibility modeling closer to addressing the *uncertain geographic context problem* (Kwan, 2012) which argues that spatial contexts are imprecise, reflecting complex constraints, decisions and behaviors. Activity-tracking data map these contexts in real-time. However, with a few exceptions (Wang, 2007), these models pay insufficient attention to individual cultural, political-economic and psychosocial processes, the impact of which on access can be profound.

Future developments

Advances in spatial modeling go hand-in-hand with methodological and theoretical developments in health geography that offer exciting opportunities and challenges for future work. From a methodological perspective, a significant trend is the increasing adoption of *Bayesian methods* that are more robust and make less restrictive assumptions than widely used frequentist methods. Bayesian methods assume that the parameters of interest are random variables, rather than fixed quantities. By combining observed data with prior beliefs about the unknown values, we can estimate these parameter values and their distributional characteristics. Health geographers were among the earliest adopters of Bayesian methods in the discipline of geography, and use of the methods has expanded dramatically with improvements in software availability and access.

Another area at the forefront of spatial modeling is analysis of *spatial and social networks* and network spaces. Many spatial methods continue to rely on Cartesian conceptions of space that are based on Euclidean distance and geographical proximity. Yet people are increasingly embedded in far-flung social networks that do not map neatly onto Cartesian spaces. Such networks have critical effects on health behaviors and outcomes. Methods of social and spatial network analysis offer important tools for studying intersections between social and geographical networks, with implications for health outcomes (Kestens et al., 2017). Furthermore, such networks compel health geographers to think beyond traditional GIS-based models of space toward spaces that are socially defined.

The explosion of *big data* from social media, web searches, tracking systems, electronic medical records and other diverse sources also presents opportunities for spatial modeling. Much of this data is *volunteered geographic information*, contributed, either intentionally or unintentionally, by individuals and heterogeneous in content. For example, Twitter data have been used to map the US obesity epidemic (Ghosh and Guha, 2013). However, existing big-data applications emphasize geovisualization; few have taken the next step to model health determinants and processes. Moreover, we know little about the validity and reliability of volunteered geographic data and their embedded social and spatial biases.

Although spatial modeling has advanced significantly in recent decades, the debates and critiques of the 1990s continue to ring true. New models more accurately represent the dynamic and relational qualities of

spatial contexts, but researchers rarely attempt to model how and why those contexts emerge and change (Pearce, 2015). Understanding contexts requires thinking about the political, economic, and decision-making processes that shape place environments at varying scales, a key point raised in earlier critiques. Researchers – for example, Larsen and Gilliland (2008) – are beginning to explore these issues by analyzing and modeling changes in food retail landscapes, but few models tie these contextual changes to people’s health-related behaviors and experiences.

Critiques also highlighted the omission in spatial models of people’s experiences and perceptions and of the recursive relationships between people and places. Although spatial modeling has inched closer to tackling these important issues by analyzing people’s daily activities and exposures, a huge gap remains. Opportunities exist to humanize spatial modeling by incorporating cultural and psychosocial factors that mediate people’s experiences in place environments. Techniques like *ecological momentary assessment* are being used to capture individuals’ health-related emotions and behaviors and link them via GIS to specific place-time settings (Mason et al., 2016). Participatory methodologies such as *participatory GIS* are also attracting interest, as researchers share model results with community members and incorporate their input and feedback to gain new understandings (Beyer and Rushton, 2009).

Conclusion

Developments in spatial modeling, GIS and geospatial technologies have greatly advanced our ability to model spatial and spatiotemporal contexts and explore their impacts on health and access to health care. Future trends are likely to include increased reliance on real-time mobility and environmental data and further development of complex and dynamic models that depict health-related interactions between people and places. At the same time, the field will continue to grapple with issues raised in earlier critiques – issues of causation, selection bias, changing political-economic contexts and human decision-making and behavior – that underpin the models we develop and the insights we glean from them. Strengthening the ties between spatial modeling and qualitative research approaches, and integrating their perspectives and methods more fully, offers exciting possibilities for making spatial modeling a more place-based endeavor.

References

- Arcaya, M., Brewster, M., Zigler, C. and Subramanian, S.V. (2012). Area variations in health: a spatial multilevel modeling approach. *Health & Place*, 18, pp. 824–831.
- Beyer, K. and Rushton, G. (2009). Mapping cancer for community engagement. *Public Health Research, Practice & Policy*, 6, pp. 1–8.
- Chaix, B., Méline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., Lewin, A., Labadi, K. and Kestens, Y. (2013). GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? *Health & Place*, 21, pp. 46–51.
- Cromley, E. and McLafferty, S. (2002). *GIS and public health*. New York: Guilford Press.
- Duncan, C., Jones, K. and Moon, G. (1998). Context, composition and heterogeneity: using multilevel models in health research. *Social Science & Medicine*, 46(1), pp. 97–117.
- Dyck, I. (1999). Using qualitative methods in medical geography: deconstructive moments in a subdiscipline? *Professional Geographer*, 51(2), pp. 243–253.
- Elliott, S. (1999). And the question shall determine the method. *Professional Geographer*, 51(2), pp. 240–243.
- Gatrell, A. C., Bailey, T. C., Diggle, P. and Rowlingson, B. (1996). Spatial point pattern analysis and its application in geographical epidemiology. *Transactions of the Institute of British Geographers*, 21(1), pp. 256–274.
- Gesler, W. (1986). The uses of spatial analysis in medical geography: a review. *Social Science & Medicine*, 23(10), pp. 963–973.
- Ghosh, D. and Guha, R. (2013). What are we “tweeting” about obesity? Mapping tweets with Topic Modeling and Geographic Information System. *Cartography & Geographic Information Science*, 40(2), pp. 90–102.
- Higgs, G. (2006). Measuring potential access to primary healthcare services. *Professional Geographer*, 58(3), pp. 294–306.

- Jerrett, M., Burnett, R. T., Kanaroglou, P., Eyles, J., Finkelstein, N., Giovis, C. and Brook, J. R. (2001). A GIS–environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environment & Planning A*, 33(6), pp. 955–973.
- Kearns, R. (1993). Place and health: towards a reformed medical geography. *Professional Geographer*, 45, pp. 139–147.
- Kestens, Y., Wasfi, R., Naud, A. and Chaix, B. (2017). “Contextualizing context”: reconciling environmental exposures, social networks, and location preferences in health research. *Current Environmental Health Reports*, 4(1), pp. 51–60.
- Knox, P. (1978). The intraurban ecology of primary care: patterns of accessibility and their policy implications. *Environment and Planning A*, 10(4), pp. 415–435.
- Kwan, M. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers*, 102(5), pp. 958–968.
- Larsen, K. and Gilliland, J. (2008). Mapping the evolution of “food deserts” in a Canadian city: supermarket accessibility in London, Ontario, 1961–2005. *International Journal of Health Geographics*, 18(7), pp. 1–16.
- Lovett, A., Haynes, R., Sunnenberg, G. and Gale, S. (2002). Car travel time and accessibility by bus to general practitioner services: a study using patient registers and GIS. *Social Science & Medicine*, 55(1), pp. 97–111.
- Lu, Y. and Fang, T. B. (2015). Examining personal air pollution exposure, intake, and health danger zone using time geography and 3D geovisualization. *ISPRS International Journal of Geo-Information*, 4(1), pp. 32–46.
- Luo, W. and Wang, F. (2003). Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region. *Environment & Planning B*, 30, pp. 865–884.
- Mao, L. (2014). Modeling triple-diffusions of infectious diseases, information, and preventive behaviors through a metropolitan social network: an agent-based simulation. *Applied Geography*, 50, pp. 31–39.
- Mason, M., Mennis, J., Zaharakis, N. M. and Way, T. (2016). The dynamic role of urban neighborhood effects in a text-messaging adolescent smoking intervention. *Nicotine & Tobacco Research*, 18(5), pp. 1039–1045.
- May, J. M. (1950). Medical geography: its methods and objectives. *Geographical Review*, 40(1), pp. 9–41.
- Mayer, J. (1983). The role of spatial analysis and geographic data in the detection of disease causation. *Social Science & Medicine*, 17(16), pp. 1213–1221.
- Mohan, J. (1989). Medical geography: competing diagnoses and prescriptions. *Antipode*, 21(2), pp. 166–177.
- Næss, Ø. and Leyland, A. H. (2010). Analysing the effect of area of residence over the life course in multilevel epidemiology. *Scandinavian Journal of Public Health*, 38, pp. 119–126.
- Norman, P., Boyle, P. and Rees, P. (2005). Selective migration, health and deprivation: a longitudinal analysis. *Social Science & Medicine*, 60(12), pp. 2755–2771.
- Owen, G., Harris, R. and Jones, K. (2016). Under examination: multilevel models, geography and health research. *Progress in Human Geography*, 40(3), pp. 394–412.
- Pearce, J. (2015). Invited commentary: history of place, life course, and health inequalities – historical geographic information systems and epidemiologic research. *American Journal of Epidemiology*, 181(1), pp. 26–29.
- Pearson, M. (1989). Medical geography: genderless and colourblind. *Contemporary Issues in Geography and Education*, 3, pp. 9–17.
- Perchoux, C., Chaix, B., Cummins, S. and Kestens, Y. (2013). Conceptualization and measurement of environmental exposure in epidemiology: accounting for activity space related to daily mobility. *Health & Place*, 21, pp. 86–93.
- Rosenberg, M. W. (1998). Medical or health geography? Populations, peoples, and places. *International Journal of Population Geography*, 4, pp. 211–226.
- Sabel, C., Boyle, P., Raab, G., Loytonen, M. and Maasilta, P. (2009). Modeling individual space-time exposure opportunities: a novel approach to unravelling the genetic or environment disease causation debate. *Spatial & Spatiotemporal Epidemiology*, 1(1), pp. 85–94.
- Smith, D., Pearce, J. and Harland, K. (2011). Can a deterministic spatial microsimulation model provide reliable small-area estimates of health behaviours? An example of smoking prevalence in New Zealand. *Health & Place*, 17, pp. 618–624.
- Steinle, S., Reis, S., Sabel, C. E., Semple, S., Twigg, M. M., Braban, C. F., Leeson, S. R., Heal, M. R., Harrison, D., Lin, C. and Wu, H. (2015). Personal exposure monitoring of PM_{2.5} in indoor and outdoor microenvironments. *Science of the Total Environment*, 508, pp. 383–394.
- Subramanian, S. V., Delgado, I., Jadue, L., Vega, J. and Kawachi, I. (2003). Income inequality and health: multilevel analysis of Chilean communities. *Journal of Epidemiology & Community Health*, 57(11), pp. 844–848.
- Townsend, N., Rutter, H. and Foster, C. (2012). Age differences in the association of childhood obesity with area-level and school-level deprivation: cross-classified multilevel analysis of cross-sectional data. *International Journal of Obesity*, 36, pp. 45–52.
- Wang, F. (2012). Measurement, optimization, and impact of health care accessibility: a methodological review. *Annals of the Association of American Geographers*, 102(5), pp. 1104–1112.
- Wang, L. (2007). Immigration, ethnicity, and accessibility to culturally diverse family physicians. *Health & Place*, 13(3), pp. 656–671.

- Widener, M. J., Farber, S., Neutens, T. and Horner, M. (2015). Spatiotemporal accessibility to supermarkets using public transit: an interaction potential approach in Cincinnati, Ohio. *Journal of Transport Geography*, 42, pp. 72–83.
- Widener, M. J. and Shannon, J. (2014). When are food deserts? Integrating time into research on food accessibility. *Health & Place*, 30, pp. 1–3.
- Zenk, S., Schulz, A. J., Matthews, S. A., Odoms-Young, A., Wilbur, J., Wegrzyn, L., Gibbs, K., Braunschweig, C. and Stokes, C. (2011). Activity space environment and dietary and physical activity behaviors: a pilot study. *Health & Place*, 17(5), pp. 1150–1161.