Annals of the American Association of Geographers

ISSN: 2469-4452 (Print) 2469-4460 (Online) Journal homepage: http://www.tandfonline.com/loi/raag21

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Mei-Po Kwan

To cite this article: Mei-Po Kwan (2018) The Limits of the Neighborhood Effect: Contextual Uncertainties in Geographic, Environmental Health, and Social Science Research, Annals of the American Association of Geographers, 108:6, 1482-1490, DOI: 10.1080/24694452.2018.1453777

To link to this article: https://doi.org/10.1080/24694452.2018.1453777

Published online: 09 May 2018.

The Limits of the Neighborhood Effect: Contextual Uncertainties in Geographic, Environmental Health, and Social Science Research

Mei-Po Kwan

Department of Geography and Geographic Information Science, University of Illinois at Urbana–Champaign

This article draws on recent studies to argue that researchers need to be attentive to the limits of the neighborhood effect as conventionally understood. It highlights the complexities of contextual influences and the challenges in accurately representing and measuring individual exposures to those influences. Specifically, it discusses the idiosyncratic and multidimensional nature of contextual effects, the temporal complexities of contextual influences, the frame dependence of exposure measures, selective mobility bias, and publication bias in neighborhood effects research. It also discusses how contextual uncertainties could be mitigated in future research (e.g., through collecting and using high-resolution space–time data and moving toward frame-independent exposure measures with results that are not affected by how data are organized with respect to space and time). *Key Words: neighborhood effect, publication bias, selective mobility bias, uncertain geographic context problem, UGCoP.*

本文运用晚近的研究, 主张研究者必须关照传统上所理解的邻里效应之侷限。本文强调情境影响的复杂性, 以及精确再现并评估个人暴露于这些影响的挑战。本文特别讨论邻里效应研究中, 情境效应的独特与多面向本质、情境影响的时间复杂性、暴露评估的架构依赖、选择性的移动偏差以及发表偏差。本文同时探讨未来的研究如何能够降低情境的不确定性 (例如通过搜集并使用高辨识率的时空数据, 以及迈向独立于架构的暴露评估, 而其研究结果不受到数据在时空方面如何组织所影响)。 *关键词： 邻里效应, 发表偏差, 选择性移动偏差, 不确定的地理情境问题 UGCoP。*

Con base en estudio recientes, este artículo sostiene que los investigadores necesitan prestar atención a los límites del efecto de vecindad, como es convencionalmente entendido. Se destacan las complejidades de las influencias contextuales y los retos de representar con exactitud y medir las exposiciones individuales a tales influencias. Específicamente, se discute la naturaleza idiosincrática y multidimensional de los efectos contextuales, las complejidades temporales de las influencias contextuales, el marco de dependencia de las medidas de exposición, el sesgo de movilidad selectiva y el prejuicio de publicación en la investigación sobre el efecto de vecindad. Se discuten también las maneras como las incertidumbres contextuales podrían mitigarse en futuras investigaciones (e.g., recolectando y usando datos de espacio–tiempo de alta resolución, y desplazándose hacia medidas de exposición de marco independiente con resultados que no sean afectados por el modo como se organizan los datos respecto del espacio y el tiempo). *Palabras clave: efecto vecinal, prejuicio de publicación, sesgo de movilidad selectiva, problema de contexto geográfico incierto, UGCoP.*

The neighborhood effect is an important notion in geographic, environmental health, and social science research. It has been the conceptual foundation for assessing the effects of environmental influences on people's behaviors or outcomes (Diez Roux 2001; van Ham et al. 2012). Neighborhood effects research to date, however, has largely used the residential neighborhood as the contextual area to examine people's environmental exposures. Due to readily available data tied to administrative units, the residential neighborhood is often conceived and operationalized as static administrative areas such as the home census tract, census block group, or postcode area. Assessing people's environmental exposures based on this conventional notion of the neighborhood effect has many limitations. It assumes that the residential neighborhood is the most relevant area affecting people's behaviors or outcomes (Kwan 2009). It assumes that people's environmental exposures and the neighborhood effect operate only through interactions among those who live in the same residential area. It ignores the critical role of time and human mobility in people's exposures to environmental influences.

Annals of the American Association of Geographers, 108(6) 2018, pp. 1482–1490 © 2018 by American Association of Geographers
Initial submission, November 2017; revised submission, March 2018; final acceptance, March 2018
Published by Taylor & Francis, LLC.

Recent publications have advanced our understanding of the limitations of the conventional notion of the neighborhood effect. One is that most people move around to undertake their daily activities and rarely stay in only one place (e.g., home) throughout the day. They often traverse the boundaries of several neighborhoods in the course of a day and thus come under the influence of many different neighborhood contexts outside of their home neighborhoods. Thus, notions of the neighborhood effect and exposure measures that ignore people's exposures to these nonresidential contexts could lead to unreliable or erroneous results (Inagami, Cohen, and Finch 2007). Another important idea from these works is that there are considerable uncertainties in the contextual areas (in both space and time) used in neighborhood effects research and that these contextual areas might not accurately capture the true and causally relevant contextual influences being studied (e.g., Howell et al. 2017; Maguire et al. 2017). These contextual uncertainties arise from various sources, one of which is the discrepancy between the true spatiotemporal configurations of environmental influences and the configurations used in past neighborhood effects studies (Kwan 2012, 2013; James et al. 2014; Chen and Kwan 2015).

Further, environmental influences often vary over space and time in highly complex ways (e.g., traffic-related air pollution). Because individual exposures to environmental influences are determined by the interactions between environmental influences and individual mobility, such exposures could face different types of contextual uncertainties. For example, individual exposure to air pollution is determined by physical contact between pollutants and humans, and both vary or move over space and time (Yoo et al. 2015; Park and Kwan 2017a; Yu et al. 2018). The influence of the food environment on people's diet and health is influenced by people's daily mobility and perceptions of different types of food outlets, as well as the opening hours of such outlets, which often are not taken into account (Widener and Shannon 2014; Chen and Kwan 2015; Wei et al. 2018). Psychosocial and neighborhood influences on drug use behavior are mediated by highly localized attitudes, cultures, and peer interactions, which are difficult to accurately represent (Mennis and Mason 2011; Epstein et al. 2014). Further, people are simultaneously exposed to multiple beneficial and harmful environmental factors that affect their health, not only during their daily lives but also throughout their life courses (Myers, Denstel, and Broyles 2016; Helbich 2018). Due to contextual uncertainties like these encountered in neighborhood effects research, findings about the effects of social and physical environments on human behaviors or outcomes are often inconsistent in past studies.

This article draws on recent studies to argue that we need to be attentive to the limits of the neighborhood effect as conventionally understood. It highlights the complexities of contextual influences and the challenges in accurately representing and measuring individual exposures to those influences. It argues that we need to move beyond the conventional notion of the neighborhood effect, which relies on using certain fixed locations (e.g., home, workplace), to assess people's environmental exposures. The very notion of the neighborhood in past neighborhood effects research is highly limiting because people move around in their daily lives and are exposed to many different spatiotemporal contexts instead of to a particular neighborhood. The neighborhood effect assessed by using the residential neighborhood, if it exists, is a special case of a much broader and general process of contextual influences that needs to be examined via a comprehensive and dynamic conceptualization of context and environmental exposures. This article argues that we need to adopt a dynamic and multicontextual conceptualization of environmental exposures that encompasses all of the relevant contexts to which individuals are exposed. It also discusses how contextual uncertainties might be addressed in future research (e.g., through collecting and using high-resolution space–time data and moving toward frame-independent exposure measures with results that are not affected by how data are organized with respect to space and time).

Contextual Effects Are Idiosyncratic

An important assumption of the conventional notion of the neighborhood effect is that people respond consistently to particular environmental influences. A fundamental characteristic of people's responses to environmental influences (and thus contextual effects), however, is that these responses are highly personal and idiosyncratic. Certain individuals might not respond to specific environmental factors as commonly assumed, and there are individual factors that significantly mediate such responses but cannot be easily captured or measured using conventional notions of neighborhoods. As Mennis and Mason (2011) argued, any given place "could be experienced and interpreted completely differently by different individuals depending on their background and past experiences" and "the influence of place on an individual's behavior operates through the individual's emotional interpretation of that place" (273). This means that how a person perceives, understands, and reacts to specific environmental factors could be peculiar and person specific. Because the same environmental factors might lead to different behaviors or outcomes due to person specific attributes, this is a major source of contextual uncertainty in the neighborhood effects literature.

Insights from recent research on drug user behavior and female sex workers lend strong support to this possibility. For instance, drug use behavior is influenced by a variety of physical and social features that might enhance or mitigate the likelihood of drug use, such as violent crime, vacant houses, vandalism, and liquor stores. In a study on the effect of real-time environmental exposure on drug users' behavior, though, Epstein et al. (2014) obtained counterintuitive results: Exposure to greater physical disorder, social disorder, and drug activity at the neighborhood level was associated with lower levels of drug craving, psychosocial stress, and negative mood. This result is counterintuitive because the common understanding is that exposure to higher levels of psychosocial stress (e.g., higher crime rate) was associated with higher levels of drug craving, not lower levels. Some highly idiosyncratic processes might be at work here, but researchers still have a very limited understanding of these processes, especially about how individuals perceive or interpret a particular neighborhood environment and why they respond to it in specific ways.

One way to improve our understanding of why different persons perceive or respond to the same neighborhood environment differently is to go beyond using objectively measured characteristics of neighborhoods to include qualitative information about people's perceptions and interpretations of their environments (e.g., Shmool et al. forthcoming). For instance, Conners et al. (2016) explored the risk environment of female sex workers in two México–U.S. border cities (Tijuana and Ciudad Juárez) using a mixed-method approach. Using participatory mapping, in-depth interviews, and activity diaries, the study found that female sex workers perceived the presence of police in an area to be a highly stressful and unsafe situation (although others might perceive the same environment as safe and feel less stress). Note that although sex work is not deemed an illegal practice in México, those engaged in the trade are subjected to police harassment and exploitation on a regular basis. Such widespread policing has created a hostile, unsafe, and criminalizing environment for female sex workers in the study areas (Conners et al. 2016).

For vulnerable social groups, as these two studies suggested, the effects of environmental influences on individual behaviors or outcomes might be the opposite when compared to those for other social groups (e.g., for these latter groups, exposure to higher levels of psychosocial stress is associated with higher levels of drug craving, not lower). We need to expand our methods—for example, using qualitative and mixed methods and people-based measures of exposure—to obtain a more nuanced and comprehensive understanding of how people perceive and respond to different contextual factors differently. In addition, it is important to take into account the multiple contexts to which people are exposed in their everyday life (Mennis and Mason 2011; Wiehe et al. 2013; Park and Kwan 2017b).

Further, neighborhood influences are multidimensional and can be contradictory, where some neighborhood features might have positive effects on the individual outcome being studied, whereas other features within the same neighborhood might have negative effects. For instance, as Myers, Denstel, and Broyles (2016) observed, neighborhoods "are not completely healthy or unhealthy, but rather can be characterized by neighborhood features that are both health-promoting and health-constraining ... where no singular aspect of a neighborhood completely explains health in individuals" (21). Even the same environmental factor can have both positive and negative impacts on individuals' health and well-being, as observed in Finlay's (2018) study on the impacts of white spaces (environmental snow and ice) on the perceived well-being of older adults. The study concluded that "white spaces both promoted and diminished the physical, mental, and social well-being" of older adults and their effects may be "contradictory" given their simultaneous healing and harmful effects on health (Finlay 2018, 77). It is thus important to take into account the complex and idiosyncratic person–place interactions and interactions between different environmental factors when examining the association between contextual influences and individual behaviors or outcomes.

The Temporality of Environmental Context and Exposure

Another important source of contextual uncertainties is the temporality of environmental influences and exposures. Because environmental influences vary over space and time and people also move over space and time and interact with environmental influences in highly complex ways, time plays a critical role in people's exposures to environmental influences (Widener, Metcalf, and Bar-Yam 2011; Wiehe et al. 2013; Widener and Shannon 2014; Yoo et al. 2015; Park and Kwan 2017a; Yu et al. 2018). The temporality of environmental exposure could manifest in different ways: (1) momentary response: exposure might only have an effect at the moment of (or shortly after) the exposure; (2) recency and time-lagged response: a contextual effect could occur a certain period of time after exposure; (3) the number of episodes (or the frequency) of exposure: the outcome is affected by how frequently a person is exposed to the environmental influence; (4) duration: the outcome is influenced by the duration of each episode of exposure; and (5) cumulative exposure: the outcome is affected by the total duration of exposure over a certain period of time or a person's life course.

Several recent studies have shed light on the importance of the temporality of context and environmental exposure in influencing individual behaviors or outcomes. For instance, Schwanen and Wang (2014) examined the effects of geographic context on momentary well-being through linking particular sections of participants' space–time paths (e.g., activity episodes) to characteristics of the sites where they were rather than to characteristics of the areas where they live. The study found that positive relations between social contacts and subjective well-being stretched across multiple timescales and depended to some extent on the duration of an activity episode and with whom the activity episode was undertaken. In another study, White et al. (2017) explored relationships between exposure to natural environments and subjective well-being through examining three types of exposure: (1) exposure in the residential neighborhood: the amount of green spaces such as parks or woodlands and blue spaces such as rivers and coast in the area around one's home; (2) visit frequency: the average frequency with which one spent one's leisure time in green and blue spaces away from home (e.g., every day, several times a week) in the last twelve months; and (3) specific visit: a single specific exposure of limited duration (e.g., a park walk). The study found that people who regularly visited nature felt that their lives were more worthwhile and that those who visited nature yesterday (a specific visit) were happier. Further, cumulative exposure had a noticeable effect: As the frequency of visits increased, the likelihood of perceiving one's life as being worthwhile also increased.

In addition to subjective well-being, the temporality of environmental exposure is important in shaping the neighborhood effect for other behaviors or outcomes. For example, Cerin et al. (2017) observed that the associations between different environmental factors (e.g., land use mix) and people's moderate-to-vigorous physical activity (MVPA) tended to vary by time of the day and day of the week. For instance, the positive associations between MVPA and land use mix, net residential density, intersection density, and the number of parks were stronger in the mornings of weekdays and the afternoon and evening periods of both weekdays and weekend days. In another study that used eighty simulated individual daily movement trajectories, Park and Kwan (2017a) compared the air pollution exposure estimates generated by four combinations of spatial and temporal attributes: (1) residence-based hourly air pollution levels, (2) residence-based daily air pollution levels, (3) movement-based hourly air pollution levels, and (4) movement-based daily air pollution levels. The results indicated that these four exposure estimates are significantly different, suggesting that researchers might over- or underestimate individual exposures if the spatiotemporal variability of air pollution levels and human mobility are not taken into account. The study argued that ignoring time and human mobility could lead to erroneous results in research on air pollution exposures.

As past studies like these have repeatedly shown, the temporality of the environmental context and exposure is important for assessing their effects on individual behaviors or outcomes accurately. Further, a particular behavior or outcome could be affected by two or more contextual temporalities—for example, both momentary exposure and the frequency of exposure were found to be important in the study by White et al. (2017), and both time of the day and day of the week were observed to be significant by Cerin et al. (2017)—and it is difficult to fully and accurately capture all pertinent contextual temporalities in neighborhood effects research. For instance, drug use at time *t* might not be influenced as much by an individual's momentary context as by the contextual environment the person experienced several (and unknown) hours before *t*. Thus, the temporality of environmental influences and exposures is another important source of contextual uncertainty.

The Frame Dependence of All Environmental Exposure Measures

No matter how environmental exposure is measured, such measurement has to rely on a particular spatial and temporal frame that organizes the data with respect to certain spatial and temporal units of analysis. The common spatial units of analysis in geographic, environmental health, and social science research are the census tract, census block group, and postcode area, whereas the common temporal units of analysis are the day, month, and year. Because the values of the contextual variables derived using different spatial and temporal units might be different, research results might differ when different units of analysis were used. Known as the frame dependence of geographic measures (Tobler 1989), this phenomenon is another important source of contextual uncertainties in neighborhood effects research.

The most well-known manifestation of the frame dependence of geographic measures is the modifiable areal unit problem (MAUP), which refers to the problem that, in the analysis of the relationships between area- or zone-based variables, research findings could be influenced by the geographic scale or the zoning scheme of the areal units for which data are organized (Openshaw 1984; Fotheringham and Wong 1991). These two components of the MAUP are referred to as the scale effect and the zoning effect, which might influence the results of neighborhood effects studies that examine the relationships between area-based contextual variables and area-based outcome variables (e.g., cancer or crime rates of census tracts). To address the MAUP, the most common methods involve identifying and adopting the best areal division, zoning scheme, or scale at which the processes being studied operate. For instance, Riva et al. (2009) addressed the MAUP through designing and using homogeneous zones in their study on the influence of the built and socioeconomic environments on walking. Mu and Wang (2008) lent support to this approach. They found that the homogeneous zones they created using scale-space clustering are effective for mitigating the MAUP and reducing model errors caused by spatial autocorrelation when using ordinary least squares regression.

Another manifestation of the frame dependence of environmental exposure measures is the uncertain geographic context problem (UGCoP), which is the problem that findings about the effects of area-based attributes (e.g., land-use mix) on individual behaviors or outcomes (e.g., physical activity) could be affected by how contextual units are geographically delineated (Kwan 2012). The UGCoP is a fundamental methodological problem because it means that analytical results can be different for different delineations of contextual units even if everything else is the same. The UGCoP, however, is often confused with the MAUP. Although they sound similar, the UGCoP is actually a different kind of problem because it is not due to the use of different zonal schemes or spatial scales. Instead, it is due to the use of arbitrary areal units (e.g., the residential census tract or postcode area) for deriving contextual variables because of the lack of knowledge about the precise spatial and temporal configurations of the environmental factors that influence individual behavior or outcome. Unlike addressing the MAUP—where the primary task is to use the best zoning scheme, areal division, neighborhood size, or geographic scale—addressing the UGCoP requires more accurate representation and delineation of the true causally relevant geographic context.

The third major manifestation of the frame dependence of environmental exposure measures is the modifiable temporal unit problem (MTUP), recently articulated by Cheng and Adepeju (2014). The MTUP refers to the problem that findings about the effects of contextual variables on individual behaviors or outcomes could be affected by how data are organized with respect to the temporal dimension. The temporal unit can be modified in three ways: (1) aggregation, where observations based on a fine temporal interval (e.g., second) are aggregated into a coarse interval (e.g., day or month); (2) segmentation, where the continuous temporal dimension is discretized into specific temporal units (e.g., weeks); and (3) boundary delimitation, where observations within a particular time period bounded by lower and upper time limits are selected for a study. Cheng and Adepeju (2014) found that there is a tendency to detect different crime clusters as the aggregation, segmentation, and temporal boundary of a space–time data set are altered. Further, they observed that temporal aggregation affects the temporal duration, size, and significance of the clusters. They stressed that researchers should be cautious when using a particular temporal scale, segmentation, and temporal boundary.

Selective Mobility Bias and Publication Bias in Neighborhood Effects Research

In addition to the frame dependence of environmental exposure measures, biases in statistical analysis and reporting augment the uncertainties that obfuscate the neighborhood effect. First, selective mobility bias could distort the results of neighborhood effects research and render them unreliable. As people move to live in new locations in the process of residential mobility, they tend to sort themselves out geographically into different types of neighborhoods with an affinity for their socioeconomic attributes. For example, "unemployed people are more likely to move into deprived neighborhoods than employed people" (Hedman and van Ham 2012, 80). The observation of a positive effect of living in a deprived neighborhood on unemployment could thus be the result of uncontrolled selective residential mobility bias, where the outcome being studied (being unemployed) is not independent of but instead contributes to the independent variables (e.g., low neighborhood socioeconomic status). Similar bias, referred to as selective daily mobility bias, can also occur when the effects of access to environmental features (e.g., green spaces) on people's health behavior (e.g., physical activity) are evaluated based on the locations people visit in their daily life. The bias stems from the fact that people's access to environmental features is measured by their mobility behavior, and the observation of a positive health effect of particular environmental features could simply reflect people's choices to visit them more frequently in their daily life rather than better access to these features (Chaix et al. 2012).

Publication bias is another factor that contributes to considerable uncertainties in neighborhood effects research. It refers to "a phenomenon in scientific reporting whereby authors are more likely to submit and journal editors are more likely to publish studies with 'positive' results (i.e., results showing a significant finding) than studies with 'negative' (i.e., supporting the null hypothesis) or unsupportive results" (Rodrigues 2013). Publication bias has been observed widely in social science and biomedical research (Kicinski 2013). For instance, an examination of 221 sociological studies conducted between 2002 and 2012 observed that only 20 percent of all of the null studies had appeared in a journal, whereas about 60 percent of studies with positive results had been published (Peplow 2014). Dickersin et al. (1987) also found that statistically significant results are three times more likely to be published than papers with null results.

Nieuwenhuis (2016) examined whether a publication bias exists in neighborhood effects research through evaluating eighty-eight studies on the relationship between neighborhood characteristics and educational outcomes (e.g., graduation rate and college attendance). The study found a substantially larger amount of studies just above the 5 percent significance level than those below it. Around the arbitrary boundary for statistical significance ($p < 0.05$),[1] there is an unusually large number of studies that are just significant when compared to the number of studies that are just insignificant, indicating that there is publication bias in the neighborhood effects literature (Nieuwenhuis 2016). This, in turn, means that the existence of the neighborhood effect might not be as robust or compelling as past studies suggest. Withholding null results has skewed this literature and could significantly distort the findings of meta-analyses that seek to increase statistical power through integrating the results of many past neighborhood effects studies.

Addressing Contextual Uncertainties in Future Research

This article highlights the limits of the neighborhood effect as conventionally understood. It suggests that we need to move beyond notions of contextual influences that rely on using specific fixed locations (e.g., home, workplace) to assess people's environmental exposures. It argues that the neighborhood effect assessed by using the residential neighborhood, if it exists, is a special case of a much broader and general process of contextual influences, which needs to be examined via a dynamic and multicontextual conceptualization of environmental exposures that encompasses all the relevant contexts to which individuals are exposed (Park and Kwan 2017b). Because the spatiotemporal dynamics of environmental influences and human mobility tend to be more important for certain types of exposure (e.g., exposure to air pollution), a helpful first step in future research is to differentiate whether the contextual effects being examined are special cases; that is, whether the residential neighborhood is the primary source of contextual influences and whether ignoring human mobility and the spatiotemporal complexities of contextual influences will seriously compromise the reliability of research results.

To mitigate the contextual uncertainties that influence the accurate assessment of people's environmental exposures and their health effects, new types of data, exposure measures, and analytical methods are needed in future research. First, location-aware geospatial technologies, ecological momentary assessment, and portable sensors can be used to collect high-resolution space–time data, such as those collected with Global Positioning System (GPS), mobile phones, accelerometers, and environmental sensors (e.g., Sagl, Resch, and Blaschke 2015; Lee and Kwan 2018; Wang, Kwan, and Chai 2018). These data can help accurately identify people's space–time trajectories, the frequency and duration of exposures, as well as their momentary responses to environmental influences, which in turn enable more accurate analysis of how contextual influences affect individual behaviors (e.g., Yang et al. 2017; Wei et al. 2018; Yu et al. 2018). When this kind of data cannot be collected or is not available, researchers should try to use small area data that are not tied to arbitrary spatial and temporal units like census tracts (e.g., public-use fine-scale raster layers of demographic and neighborhood characteristics generated from original data points and provided by census bureaus). Using these data can help mitigate the MAUP, the UGCoP, and the MTUP.

Second, exposure measures can be improved along several directions. One fruitful direction is to more accurately delineate the true spatiotemporal context of individuals through constructs like individual activity spaces (e.g., Cerin et al. 2017; Howell et al. 2017). Note that although some of the nuances and dynamics related to environmental exposures can be taken into account through appropriate modeling approaches (albeit constrained by considerations of parsimony and model specification), researchers normally have little or no prior knowledge about the precise spatiotemporal configuration of the true and causally relevant geographic context, the accurate delineation of which is one of the most important tasks in future research. Further, using specific exposure measures to capture various temporalities of contextual influences (e.g., White et al. 2017) and enhancing exposure measures with qualitative information about people's perceptions and interpretations of their environments seem helpful for mitigating the UGCoP and selective daily mobility bias (e.g., Chaix et al. 2012; Conners et al. 2016; Shmool et al. forthcoming).

Further, it is important to develop frame-independent exposure measures that will produce results unaffected by how data are organized with respect to space and time. Past research on individual accessibility indicates that space–time accessibility measures are frame-independent: Analytical results obtained with these measures were not affected by either the zoning scheme or spatial scale (Weber and Kwan 2003; Kwan and Weber 2008). These measures capture each person's use of and movement across space and time based on detailed data of the person's daily activities and trips (Kwan 1998, 1999). Drawing on concepts with affinity to space–time accessibility measures, recent studies on environmental exposures have begun to use delineations like individual activity space to assess people's environmental exposures (e.g., Wang, Kwan, and Chai 2018; Zhao, Kwan, and Zhou 2018). Their results suggest that activity space, when appropriately delineated, can be used to derive frame-independent exposure measures.

Third, researchers need to use analytical methods and modeling approaches that can take into account various contextual uncertainties. For instance, adopting longitudinal and life-course approaches that take people's residential histories and experiences over time into account is helpful for addressing selective residential mobility bias and the cumulative exposure to environmental circumstances over life (e.g., Pearce this issue). Suitable dynamic models such as lagged and time series models with time-dependent or time-varying effects can be used to examine the cumulative, recency, and time-lagged response of contextual exposures.

Acknowledgments

An earlier version of this article was presented at the Melinda S. Meade Distinguished Lecture at the 2017 Annual Meeting of the American Association of Geographers in Boston and in the Evelyn L. Pruitt Lecture at Louisiana State University on 21 April 2017. I thank Tim Schwanen and three anonymous reviewers for their helpful comments and Jue Wang for his capable research assistance.

Funding

This article draws on findings from research projects supported by the U.S. National Institutes of Health (R01DA028692-01), the U.S. National Institute of Drug Abuse, and the University of Illinois Research Board. I was supported by a grant from the National Natural Science Foundation of China (#41529101) and a John Simon Guggenheim Memorial Foundation Fellowship while writing this article.

Note

1. Note that although the p value actually expresses the probability of a Type I error (incorrect rejection of a null hypothesis), a p value of 0.05 is often used in statistical tests as a cutoff value for statistical significance; a p value larger than 0.05 is taken to mean that the effect is not statistically significant (Mark, Lee, and Harrell 2016).

ORCID

Mei-Po Kwan http://orcid.org/0000-0001-8602-9258

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MEI-PO KWAN is a Professor in the Department of Geography and Geographic Information Science at the University of Illinois at Urbana–Champaign, Urbana, IL 61801. E-mail: mpk654@gmail.com. Her research interests include environmental health, human mobility, sustainable transport and cities, GIScience, and GIS methods in geographic research.