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RESEARCH ARTICLE



Uncertainties in the geographic context of health behaviors: a study of substance users' exposure to psychosocial stress using GPS data

Mei-Po Kwan ^a, Jue Wang ^a, Matthew Tyburski^b, David H. Epstein^b, William J. Kowalczyk^c and Kenzie L. Preston^b

^aDepartment of Geography and Geographic Information Science, University of Illinois at Urbana-Champaign, Urbana, IL, USA; ^bTreatment Section, Clinical Pharmacology and Therapeutics Research Branch, Intramural Research Program, National Institute on Drug Abuse, Baltimore, MD, USA; ^cDepartment of Psychology, Hartwick College, Oneonta, NY, USA

ABSTRACT

This study examined how contextual areas defined and operationalized differently may lead to different exposure estimates. Substance users' exposures to environmental stress (in terms of two variables: community social economic status and crime) were assessed from global positioning systems (GPS) data. Participants were 47 outpatients with substance use disorders admitted for methadone maintenance at a research clinic in Baltimore, Maryland. From 35.2 million GPS tracking points, we compared 7 different methods for defining activity space. The different methods yielded different exposure estimates, which would lead to different conclusions in studies using only one method. These results have important implications for future research on the effect of contextual influences on health behaviors and outcomes: whether a study observes any significant influence of an environmental factor on health may depend on what contextual units are used to assess individual exposure.

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Geographic context; contextual uncertainties; substance use; GPS data; the uncertain geographic context problem

1. Introduction

Much of environmental health research is concerned with whether and how social and physical environments affect health (Berkman and Kawachi 2000; Diez-Roux 2001; Macintyre *et al.* 2002; Myers *et al.* 2016). To examine whether an environmental factor has a significant influence on a specific health behavior or outcome, it is first necessary to accurately measure individual exposure to the relevant environmental factor. An important issue in this measurement process is to identify the appropriate geographic area to be used as the contextual unit for deriving the values of various environmental variables (e.g. neighborhood socioeconomic status [SES]). Contextual areas in most studies in the past tend to be based on conventional delineations of people's residential neighborhood, which is often identified in terms of administrative units such as census tracts or postal code areas (Arcaya *et al.* 2016). Common assumptions underlying these conventional delineations of contextual areas include the neighborhood of residence is

the most relevant area affecting health behaviors and outcomes, and neighborhood effects operate only through interactions among those residing within the same neighborhood unit. Further, individuals who live in the same areal unit are assumed to experience the same level of contextual influences, regardless of where they actually live within the area or how much time they spend outside their neighborhood of residence.

Using administrative units as the basis for evaluating neighborhood effects is convenient because they are often tied to data from censuses and surveys that can be used to derive contextual measures. However, people's exposures to influences from their social and physical environments are determined by where they go and how much time they spend there as they move around to undertake their daily activities (Cummins *et al.* 2007; Kwan 2009, 2013; Matthews 2008; Widener *et al.* 2013). People's activities (and thus environmental exposures) do not take place at one time point and wholly within any static, administratively bounded areal unit like census tracts or blocks. Residential location is one of the places where people spend their time, but for most people, the residential neighborhood does not capture many of their daily activities or the locations of these activities. In light of this, people's movement in space and time should be taken into account in order to more accurately estimate their environmental exposures and the effects of various contextual factors on their health behaviors and outcomes.

The methodological issue arising from the use of conventional contextual areas, largely in the form of static administrative areas, in health and geographic research has been recently articulated as the uncertain geographic context problem (UGCoP) (Kwan 2012). It refers to the problem that inferences about effects of area-based attributes (e.g. land-use mix) on individual behaviors or outcomes (e.g. physical activity) may be affected by how contextual areas or neighborhoods are geographically delineated. The problem 'arises because of the spatial uncertainty in the actual areas that exert contextual influences on the individuals being studied and the temporal uncertainty in the timing and duration in which individuals experienced these contextual influences' (Kwan 2012). As no researcher has complete and perfect knowledge of the 'true causally relevant' geographic context, all previous studies that used area-based contextual variables to explain individual behaviors or outcomes face the problem.

The UGCoP argument is strongly corroborated by findings from recent studies on environmental influences on body weight (James *et al.* 2014; Zhao *et al.* 2018), food access and its effects on health (Widener *et al.* 2013; Chen and Kwan 2015) and individual exposure to air pollution (Yoo *et al.* 2015; Dewulf *et al.* 2016; Park and Kwan 2017; Yu *et al.* 2018). These studies indicate that the UGCoP is a significant methodological problem in geographic and health research that seeks to understand how environmental factors affect health behaviors and outcomes. This paper seeks to contribute to this literature by showing how uncertainties in geographic context may affect exposure measures in a study of substance users' exposure to psychosocial stress using global positioning systems (GPS) data. It extends conventional concepts of neighborhood to a broader understanding of context based on people's activity spaces (i.e. the actual locations where people undertake their daily activities) (Golledge and Stimson 1997). It explores how context defined and operationalized differently may lead to different exposure estimates and different conclusions about their effects on health.

Specifically, the study examines substance users' exposure to psychosocial stress evaluated with two variables: a composite measure of community SES and crime. It uses a GPS dataset collected from outpatients with substance use disorders admitted for methadone maintenance at a research clinic in Baltimore, Maryland (Epstein *et al.* 2014). From 35.2 million GPS tracking points (GTPs), 7 contextual areas based on the notion of activity space are delineated for 47 participants. Measures of these participants' exposure to psychosocial stress are derived with these seven contextual areas, which are GTPs, GPS trajectory buffers (GTBs), standard deviational ellipses (SDEs) with one or two standard deviation(s) [SD(s)] (SDE1, SDE2), minimum convex polygons (MCPs), kernel density surfaces (KDSs) and home buffers (HBs). The results indicate that different delineations of contextual areas yield different exposure estimates, which vary considerably across the participants and exposure measures. These results have important implications for future research on the effect of contextual influences on health behaviors and outcomes: whether a study observes any significant influence of an environmental factor on health may depend on what contextual units are used to assess individual exposure.

2. Environmental influences on substance use behavior

Substance use and addiction are public health concerns that have wide-ranging social consequences. Considerable research has been conducted to identify risk and protective factors at the psychological and social levels (Boardman *et al.* 2001; Molina *et al.* 2012; Brenner *et al.* 2013). These factors generally fall into two broad categories: those that pertain to individuals and their interpersonal environments (e.g. attitudes and influences from peer groups) and those that reflect societal contextual conditions (e.g. neighborhood disorganization and economic deprivation).

Much of the early work in this area focused on individuals' own characteristics and those of their families and peers (Hawkins *et al.* 1992; Galea *et al.* 2004). Recent studies emphasize the additional impact of the neighborhood environment or context (which were largely derived from census-tract data) based on the hypothesis that neighborhoods can contribute to problem behavior (Sampson *et al.* 2002; Galea *et al.* 2005). For instance, researchers have observed associations between the physical and social environments and substance dependence (Kadushin *et al.* 1998) and between neighborhood disadvantage and the availability of illegal substances (Storr *et al.* 2004). Studies have also found that the association between neighborhood deprivation and substance use was partly mediated by differences in the level of psychological distress (Boardman *et al.* 2001). Many of these findings suggest that the influence of neighborhoods is causal. Specifically, neighborhood environment may significantly influence stress levels, which may influence substance use (Kwan *et al.* 2008; Mennis and Mason 2010, 2011; Brenner *et al.* 2013).

On the whole, however, research findings on the effect of neighborhood characteristics on illicit substance use are inconsistent. For instance, while several studies indicate that differences in neighborhood disadvantage – variously defined in terms of one or more characteristics based on census tracts, such as poverty status or an index capturing several community features – provide part of the explanation for higher levels of illicit substance use among adolescents and adults (Boardman *et al.* 2001; Hoffman 2002),

others found that such neighborhood disadvantage measures are not significantly associated with adolescent substance use (e.g. Allison *et al.* 1999). Thus, among the many sociogeographic factors identified as relevant for illicit substance use and abuse, the role of neighborhood context remains less clear than those of individual, family and peer risk factors. While it is recognized that certain environmental or contextual conditions may invoke substance use among addicted individuals, there are significant conceptual and measurement issues in past studies that call for further investigation.

One important issue, as noted above, is that these studies have usually relied on exposure measurements based on people's residential neighborhoods, which are static and administratively bounded. Researchers have recently begun to adopt a dynamic notion of sociogeographic context (Kwan *et al.* 2008; Kwan 2009; Mason and Korpela 2009; Mennis and Mason 2011; Mennis *et al.* 2016; Epstein *et al.* 2014) and to use new data collection methods and analytical techniques (e.g. GPS data that tie to real-time ecological momentary assessment [EMA] data and geographic information systems [GIS]) (e.g. Mason *et al.* 2009; Mason and Korpela 2009).

This study uses a GPS dataset collected from substance users in Baltimore, Maryland, to explore how estimates of substance users' exposure to psychosocial stress may be affected by the contextual areas used to derive the exposure measures. It examines exposure to psychosocial stress using two variables: a composite measure of community SES and crime. The study seeks to shed light on the inconsistencies in previous findings and to contribute to the nascent literature on the UGCoP in health and GIScience research (e.g. James *et al.* 2014; Park and Kwan 2017; Shafran-Nathan *et al.* 2017; Helbich 2018; Wei *et al.* 2018; Zhao *et al.* 2018).

3. Data and methods

3.1. Data collection and preprocessing

The GPS dataset used in this study was collected in Baltimore, Maryland, from 2009 to 2011, using methods similar to those we described in a published pilot study with data collected in 2008–2009 (Epstein *et al.* 2014), but in a larger sample (Preston *et al.* 2018). The purpose of the project was to assess the associations between participants' real-time environmental psychosocial stress exposure and their substance use behavior. Participants were outpatients admitted for methadone maintenance at a research clinic in Baltimore. Eligibility criteria for enrollment were aged 18–65, physical dependence on opioids and evidence of cocaine and opiate use (self-report and urine). Exclusion criteria were any psychotic disorder listed in the *Diagnostic and Statistical Manual of Mental Disorders*, 4th Edition (DSM-IV), history of bipolar disorder or current major depressive disorder; current DSM-IV dependence on alcohol or sedative-hypnotics; cognitive impairment severe enough to preclude informed consent or valid self-report; and medical illness that would compromise participation. The Institutional Review Board of the National Institute on Drug Abuse approved the study, and participants gave written informed consent before enrollment. All data were covered by a Federal Certificate of Confidentiality.

Each participant carried a small GPS logger at all times during the study period. The GPS devices were set to log geolocation (latitude, longitude and altitude) every 20 m or

every 15 min, whichever came first. This means that the GPS tracking data were not collected evenly in space and time but rather selectively: a location was logged if a participant moved more than 20 m from the previously recorded location, or a location was logged every 15 min if the participant did not move more than 20 m from the previously recorded location within the period. Each participant also carried a PalmPilot PDA at all times and was trained to use it as an electronic diary (ED), which provided data for the EMA component of the project. An ED entry was initiated whenever the participant (1) used any substance (e.g. cocaine, heroin or other opioid, marijuana, an amphetamine, benzodiazepines or alcohol) outside of a medical context or (2) felt overwhelmed, anxious or stressed more than usual. In addition to these event-triggered entries, participants responded to randomly timed prompts via their PDAs three times per day to report their mood, stress level, environmental setting, activities and degree of substance craving.

Analyses reported in this paper are based on a subsample of 47 participants from the larger multi-week project because of the computational intensity of the geospatial analysis involved. For these 47 participants, there were 35.2 million GTPs and the average tracking period is 107 days. Note that the tracking periods among these participants varied considerably: two participants had the shortest tracking period of 19 days, while two other participants had very long tracking periods that exceeded 200 days. Further, although the participants were outpatients admitted for methadone maintenance at a research clinic in the city of Baltimore, some of them spent considerable time outside the city. We thus expanded the study area to include the entire state of Maryland, which covers more than 90% of the total GPS records in the subsample.

Before data analysis was performed, a Python program was implemented to ensure consistency and eliminate errors in the GPS data. Each GPS track was checked to ensure proper temporal order and presence of at least two GPS points. Duplicate points were eliminated. Each track was also checked to make sure it met the criterion that a location was logged if a participant moved more than 20 m from the previously logged location, or every 15 min otherwise. Further, to reduce computational complexity, the duration between any pair of consecutive GPS records was assigned to the first point if a participant did not move more than 20 m during the period. This simplification is acceptable since 20 m is a small distance relative to the area of the contextual units delineated in the study.

3.2. Contextual variables

Past health studies have identified causal links between contextual influences and people's health behaviors. Particularly salient for substance use are social cohesion, social capital and collective efficacy, each of which can be protective against substance-related problems (Boardman *et al.* 2001; Latkin *et al.* 2005; Brenner *et al.* 2013). Conversely, neighborhoods that are low in these dimensions and have high crime rates tend also to have high rates of substance-related problems. In this study, we used two constructs to capture potential contextual influences on the participants. The first construct is community SES; the second is crime. Each is useful for representing social cohesion, collective efficacy and social disorder (e.g. Stahler *et al.* 2007; Mennis and Mason 2011; Epstein *et al.* 2014).

Community SES was operationalized in this study as a composite socioeconomic index (CSI) based on the modified Darden–Kamel composite index developed by Darden *et al.* (2010). It uses nine variables from census data and assigns a higher score to communities with higher SES. The nine variables are the percentage of residents with university degrees, median household income, the percentage of managerial and professional positions, median value of dwelling, median gross rent of dwelling, the percentage of homeownership, the percentage of households with vehicle, the percentage of population below poverty (reverse scored) and unemployment rate (reverse scored). The CSI was calculated as the sum of Z scores of the nine variables by using the following formula:

$$CSI_i = \sum_{j=1}^n \frac{V_{ij} - V_{j\ MD}}{SD(V_{j\ MD})} \quad (1)$$

where CSI_i is the composite SES index for census tract i ; n is the number of variables for the index (it is 9 for the modified Darden–Kamel composite index), V_{ij} is the j th variable for a given census tract i , $V_{j\ MD}$ is the mean of the j th variable for all census tracts in the state of Maryland and $SD(V_{j\ MD})$ is the SD of j th variable for all census tracts in Maryland. Since the GPS data were collected from 2009 to 2011, the American Community Survey census tract data of 2010 were used in this study to calculate the CSI for each census tract in Maryland (this was the finest resolution available on the website of the US Census at the time when analyses for this paper were performed). Figure 1 shows the CSI scores for all census tracts in Maryland.

Crime data were obtained from the Baltimore Neighborhood Indicator Alliance website, which provides data on two relevant measures: rate of violent crime and rate of general crime, each taken from reports to the Baltimore Police Department. Violent crimes include murder and nonnegligent homicide, forcible rape, aggravated assault

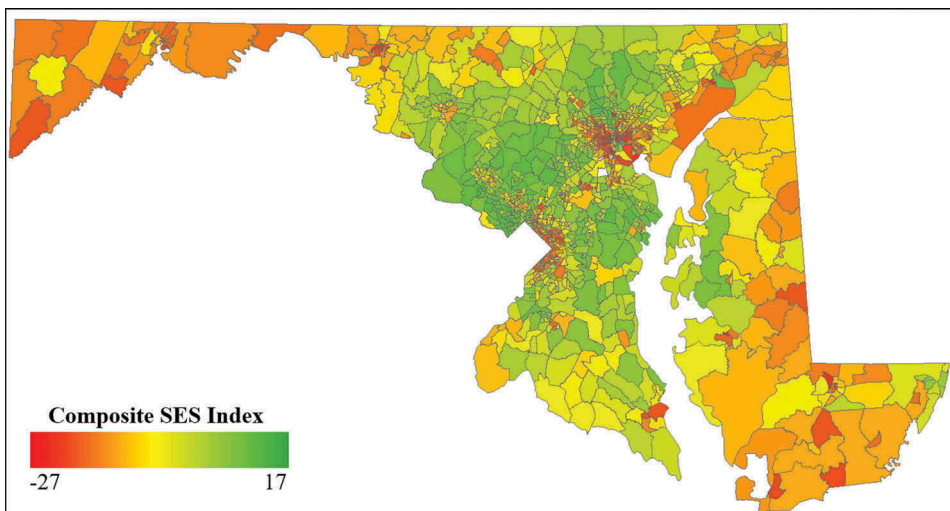


Figure 1. Composite SES index (CSI) for census tracts in Maryland. A high CSI score reflects better SES of a census tract and a low CSI score reflects lower SES of a census tract.

and robbery. General crime includes violent crime plus burglary, larceny-theft, motor vehicle theft and arson. Both violent and general crime rates are based on the number of relevant crimes per 100,000 residents in a particular community. This study used the broader category of general crime as the measure of crime. Since crime data at the level of census tract are available only for the city of Baltimore but not for the state of Maryland, analyses in this paper that used crime data focused only on Baltimore City.

3.3. Delineations of contextual areas and deriving exposure measures

To assess participants' exposure to psychosocial stress (measured by the CSI and crime), 7 delineations of individual contextual areas were implemented for the 47 selected participants – 6 using their GPS data, one using their home location. The six GPS-based delineations are GTPs, GTBs, SDEs with one or two SD(s) (SDE1, SDE2), KDSs and MCPs. The home-based delineations are HBs. [Figure 2](#) illustrates five of these contextual areas for one participant (excluding GTP and HB to protect the participant's privacy). Appropriate methods of temporal or spatial interpolation were used to derive exposure measures from these contextual areas for each participant, and the contextual variables (CSI and crime) were standardized or normalized to ensure comparability among the participants. All data processing and analyses were performed with ArcGIS.

1. *GTPs* – Participants' exposure to psychosocial stress was first assessed using their GTPs. Because the original GPS points are temporally uneven, a Python program was developed to interpolate data, using these steps: (1) The time difference between every pair of consecutive GPS points was calculated; (2) if the difference was longer than 1 s (say, N seconds), the program used linear interpolation to insert $N - 1$ more points evenly between the two. After this, each participant's GPS tracks had one point every

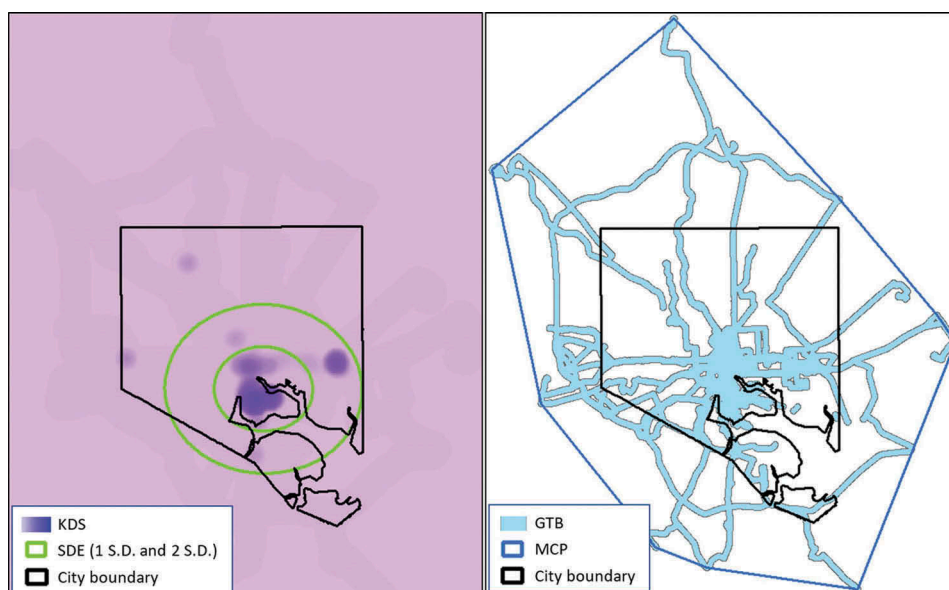


Figure 2. The contextual areas of a participant delineated by different methods (GTP and HB are not included for privacy concern).

second. Further, each of the contextual variables (CSI and crime) was computed as the sum of its values at all GPS points divided by the number of GPS points for each participant (this step standardized the contextual variable because the number of GPS points was different across participants).

2. *GTBs* – A GTB was created for each participant by covering the participant's GPS trajectories with a 200-m buffer area. Because this buffer area covers all the locations that a participant visited or passed during GPS logging, it can be used to assess participants' exposure to psychosocial stress in their daily life. This was done with a weighted sum of the contextual values based on the area of each census tract that was within a participant's GTB.

3 and 4. *SDEs at one and two SD(s) (SDE1 and SDE2)* – The SDE has been used in prior studies to delineate individual activity space and derive exposure measures (e.g. Sherman *et al.* 2005; Rainham *et al.* 2010). An SDE captures the geographic distribution and directional trend of a series of points and was derived in the following manner (Arcury *et al.* 2005; Wong and Lee 2005). First, the mean center of a participant's GPS points was derived. Then, the coordinates of each point in the set were transformed so that the center of the transformed coordinates became (0,0). The ellipse was finally obtained based on one or two SD(s) of the distances between each point and the transformed mean center along the rotated major and minor axes of the point set (Sherman *et al.* 2005). Since some past studies used one SD SDE while other studies used two, we derived both for comparison. For each participant, an SDE at one SD (SDE1) includes approximately 68% of the participant's GPS points within its boundary, while an SDE at two SDs (SDE2) contains approximately 95% (Sherman *et al.* 2005). To assess participants' exposure to psychosocial stress, a weighted sum of the values of a contextual variable (e.g. crime) was used, based on the area of each census tract that was within a participant's SDE.

5. *Time-weighted KDSs* – The KDS has also been used in prior studies to represent activity space and derive exposure measures. It is a density surface derived from the location of a set of points (and an associated weight such as the population at each point) using a kernel function and a predetermined search radius (or bandwidth). To generate a KDS for each participant in the study, a nonparametric kernel estimation method and a bandwidth of 1000 m was used. The 1000-m bandwidth avoids two issues associated with smaller bandwidths. First, the resulting density surface obtained with smaller bandwidths may approximate the GPS buffers, since the density surface is derived with only a few adjacent GPS points. Second, the resulting density surface obtained with smaller bandwidths may consist of many small discrete areas, because many cells in the raster surface will have 0 values, given that the smoothing kernel function covers only a small area and thus falls off rapidly. Based on some experiments with different bandwidth values, we found that 1000 m worked well for our dataset and study area. Using this bandwidth, the KDSs were generated based on the duration spent at each GTP as the weight on a raster layer with a spatial resolution of 100×100 m. To utilize the estimated kernel density values as the weight at each GTP for calculation of participants' contextual exposures, the raster cells with a density value larger than 0 were converted to points in a point-feature vector layer. The weighted sum of the values of a contextual variable (e.g. crime) was finally derived based on the kernel density value at each point.

6. *MCPs* – The MCP for a participant is the smallest convex polygon that contains all of the person's GTPs. To assess participants' exposure to psychosocial stress using the MCP, a weighted sum of the values of each contextual variable was derived, based on the area of each census tract that was within a participant's MCP.

7. *HBs* – Home location and residential neighborhood are the most commonly used contextual areas in past studies. Each participant's home location was used to construct a 1-km HB area for assessment of residential exposure to psychosocial stress. Note that information about participants' home location was not available in the dataset due to the need to protect their geoprivacy and data confidentiality. We inferred home locations based on the assumption that people tend to spend most of their time at or around their home location (e.g. sleep time and the time spent on home-based activities). This was achieved by using the total amount of time participants spent at and around their GTPs using the time-weighted KDS (which is a raster layer at the spatial resolution of 100×100 m): the location where a participant spent most time is treated as his/her home location. To assess participants' exposure to psychosocial stress using the home location buffer, a weighted sum of the values of each contextual variable was derived, based on the area of each census tract that was within a participant's home location buffer.

All seven contextual areas described above were implemented to derive measures of individual exposure to different levels of SES (CSI), but only the first six were used to evaluate exposure to crime. This was because the inferred home locations of many participants were outside Baltimore City, and crime data at the level of census tract were available only within the city.

4. Analysis and results

4.1. Comparison of the size of different contextual areas

We begin our analysis by comparing the size of 5 of the contextual area delineations described in the last section (Figure 3). The HBs had the same area for all participants because they were defined as 1-km buffer areas, and the GTPs method did not generate

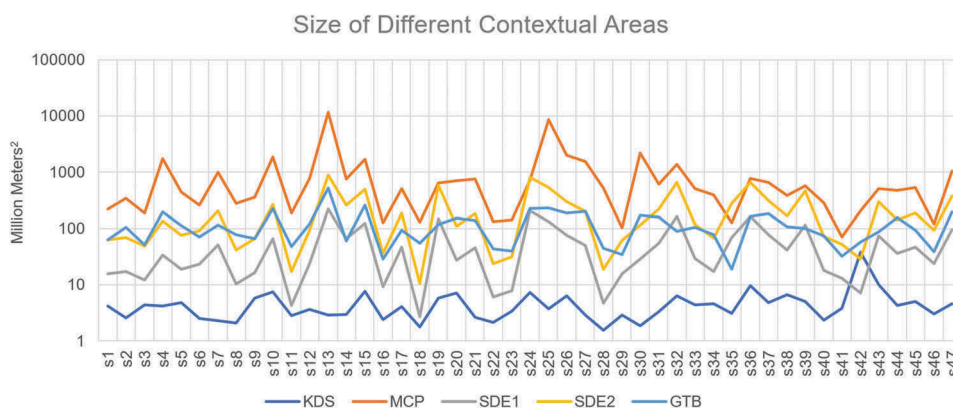


Figure 3. Comparison of the size of different contextual areas in logarithmic scale for the 47 participants. The vertical axis that indicates the size of contextual areas is on a logarithmic scale.

any area. Of the other five methods, four produced polygons with explicit boundaries (GTB, SDE1, SDE2, MCP) such that their areas were straightforward to calculate. For KDS (a continuous surface with different density values for different cells), the area was derived using a threshold density value that separates the top quantile from the four quantiles below it, and cells with values higher than the threshold were considered part of the contextual area.

The KDSs had sizes similar to the HBs, but with some variation across participants. The other four contextual areas varied considerably more across participants. MCP tended to be largest while SDE1 tended to be the smallest. While the sizes of these four contextual areas were largely different from each other, their differences among the participants tended to correlate (i.e. a participant with a small SDE1 would also have a small MCP, and vice versa). It is not surprising that the sizes of the SDE1 and SDE2 were highly correlated, because they were generated with the same method. However, the correlation between areas of MCP and GTB was somewhat surprising. It may reflect the fact that both methods generated polygons that included all GTPs.

The Wilcoxon signed rank test was used to evaluate the differences in size among these five contextual areas. It is a nonparametric equivalent of the paired-sample *t*-test; it does not assume normality in the data and thus can be used when this assumption is violated. Table 1 shows the results: the sizes of the five contextual areas were significantly different from each other. Note that the sizes of these five contextual areas varied considerably for some participants but much less for other participants. Participants with spatially dispersed GPS trajectories tended to have MCPs that were much larger than other delineations of contextual areas (and thus also tended to have the largest variation among the five contextual areas). Conversely, participants with relatively circumscribed GPS trajectories had smaller and similarly sized contextual areas. This could have practical implications, because the size of the contextual areas can affect estimates of exposure (e.g. to crime), as we discuss in the next section.

4.2. Comparison of individual exposure to community SES

The community SES index (CSI) described earlier was used as a surrogate to assess participants' exposure to the psychosocial stress presumed to accompany social disorder. We used all of the 7 contextual areas to derive 7 CSIs for each of the 47 participants. As shown in Figure 4, values of CSI in the participants' activity spaces varied from -23 to

Table 1. Wilcoxon signed rank correlation test of the size of different contextual areas.

Measurement pair	Z	Asymp. sig. (two-tailed)
MCP-KDS	-5.968 ^a	<0.001
SDE1-KDS	-5.714 ^a	<0.001
SDE2-KDS	-5.947 ^a	<0.001
GTB-KDS	-5.968 ^a	<0.001
SDE1-MCP	-5.968 ^b	<0.001
SDE2-MCP	-5.767 ^b	<0.001
GTB-MCP	-5.968 ^b	<0.001
SDE2-SDE1	-5.968 ^a	<0.001
GTB-SDE1	-5.259 ^a	<0.001
GTB-SDE2	-3.037 ^b	0.002

^aBased on negative ranks.

^bBased on positive ranks.

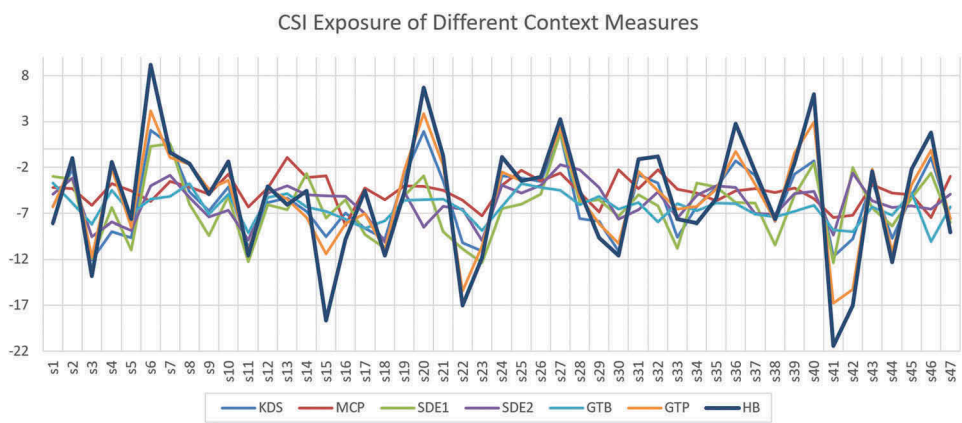


Figure 4. Comparison of CSI exposures based on different contextual areas for the 47 participants.

10, where a higher CSI score indicates higher SES, and vice versa. Variation among participants was largest with the HBs ($SD = 6.54$) and the GTPs ($SD = 4.91$), and smallest with MCP ($SD = 1.55$) and GTB ($SD = 1.52$). This is perhaps because delineations other than the HBs and the GTP are relatively large polygons that cover many census tracts, attenuating the influence of extremes.

To explore how values of the CSI varied within participants, we examined variations in the SD of the CSI in Figure 5. The figure shows that the CSIs obtained with the seven contextual areas for three participants (s6, s20 and s42) had very large SDs, while the CSI for three other participants (s12, s26 and s35) had very small SDs. We further investigated these six participants using geovisualizations, whose results are discussed here but cannot be shown due to IRB requirements to protect participants' privacy. All three participants with large CSI SDs had relatively small activity spaces with fairly even coverage within those spaces. On the other hand, two out of the three participants with small CSI SDs had relatively large activity spaces with strong directional trends. As suggested earlier, larger contextual areas cover many census tracts and the CSI derived with them tend to vary less.

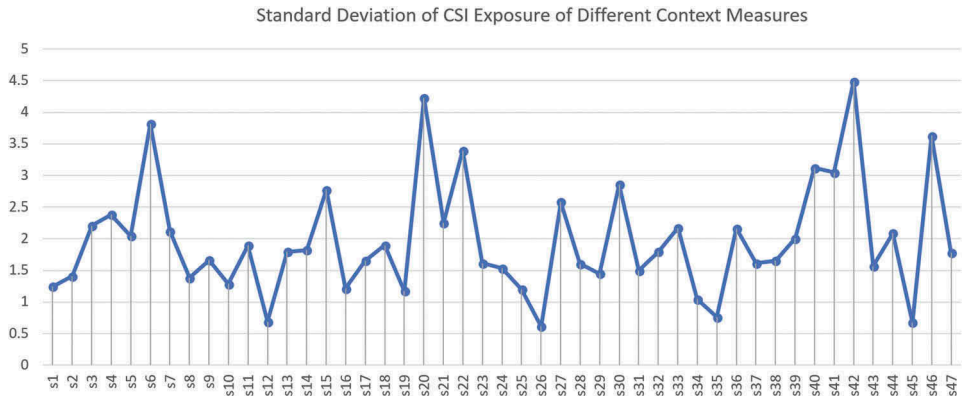


Figure 5. Standard deviation of CSI exposures based on different contextual areas for the 47 participants.

These results indicate that variation in CSI exposure can vary depending on the method used to define contextual areas – not only across participants but also for the same participant. A Wilcoxon signed rank test (Table 2) indicated that 6 out of 15 pairs of CSI estimates were significantly different from each other: MCP versus KDS, SDE1 versus KDS, SDE1 versus MCP, SDE2 versus MCP, GTB versus MCP and GTP versus SDE1. Note that four of these six pairs involve MCP and three of them involve SDE. Also note that all of the six pairs involving the HBs were not significantly different, which means that the CSI derived with the HBs were not significantly different from the CSI assessed using the other six contextual areas. This result may be due to the fact that the HBs were defined around the locations where participants spent most of their time, and participants' home location also figured prominently in the definitions of the other contextual areas. For instance, the GTPs, GPS buffers (GTB), SDEs (SDE1 and SDE2) and time-weighted KDSs tended to be skewed toward the place where participants spent the most time (i.e. their home location) because this place was heavily weighted in the data set.

4.3. Comparison of individual exposure to crime

Figure 6 shows estimates of general crime exposures as assessed by six of the contextual areas (HBs were not included in this analysis because the inferred home locations of many participants were outside Baltimore City, and crime data at the level of census tract were available only within the city). Exposures assessed with KDS (SD = 19.43) and GTP (SD = 26.17) had the largest variations among the 47 participants; exposures assessed with MCP (SD = 5.88) had the least variation.

Wilcoxon signed rank tests (Table 3) showed that 11 out of the 15 pairs of crime-exposure estimates were different from each other: MCP versus KDS, SDE1 versus KDS, SDE2 versus KDS, SDE1 versus MCP, SDE2 versus MCP, GTB versus MCP, GTP versus MCP, GTB versus SDE1, GTP versus SDE1, GTB versus SDE2 and GTP versus SDE2. Exposures for only four pairs of contextual areas were not significantly different: GTB versus KDS, GTP versus KDS, GTP versus GTB and SDE2 versus SDE1.

Table 2. Wilcoxon signed rank correlation test of CSI exposures based on different contextual areas.

Measurement pair	Z	Asymp. sig. (two-tailed)
MCP–KDS	–2.085 ^a	0.037
SDE1–KDS	–2.032 ^b	0.042
SDE2–KDS	0.000 ^c	1.000
GTB–KDS	–0.995 ^b	0.320
GTP–KDS	–1.884 ^a	0.060
SDE1–MCP	–3.026 ^b	0.002
SDE2–MCP	–3.418 ^b	0.001
GTB–MCP	–5.492 ^b	<0.001
GTP–MCP	–1.058 ^b	0.290
SDE2–SDE1	–1.545 ^a	0.122
GTB–SDE1	–0.296 ^a	0.767
GTP–SDE1	–2.032 ^a	0.042
GTB–SDE2	–1.778 ^b	0.075
GTP–SDE2	–1.090 ^a	0.276
GTP–GTB	–1.640 ^a	0.101

^aBased on negative ranks.

^bBased on positive ranks.

^cThe sum of negative ranks equals the sum of positive ranks.

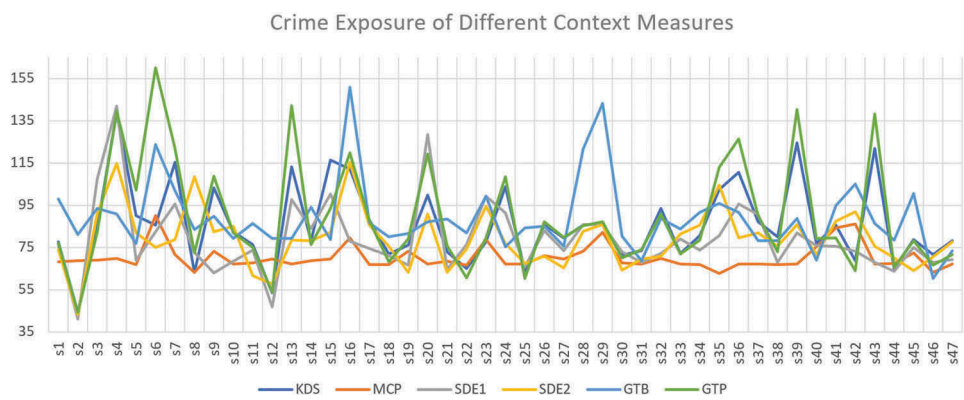


Figure 6. Comparison of crime exposures based on different contextual areas for the 47 participants.

Table 3. Wilcoxon signed rank correlation test of crime exposures based on different contextual areas.

Measurement pair	Z	Asymp. Sig. (two-tailed)
MCP–KDS	−4.635 ^a	<0.001
SDE1–KDS	−3.005 ^a	0.003
SDE2–KDS	−2.730 ^a	0.006
GTB–KDS	−1.217 ^b	0.224
GTP–KDS	−1.355 ^b	0.176
SDE1–MCP	−3.365 ^b	0.001
SDE2–MCP	−3.831 ^b	<0.001
GTB–MCP	−5.894 ^b	<0.001
GTP–MCP	−4.561 ^b	<0.001
SDE2–SDE1	−0.224 ^a	0.823
GTB–SDE1	−3.291 ^b	0.001
GTP–SDE1	−2.794 ^b	0.005
GTB–SDE2	−3.683 ^b	<0.001
GTP–SDE2	−2.593 ^b	0.010
GTP–GTB	−0.349 ^a	0.727

^aBased on positive ranks.
^bBased on negative ranks.

Figure 7 shows the SDs of general crime exposures assessed by the 6 contextual areas for the 47 participants. Three participants (s4, s6 and s16) had very high SDs; two participants (s31 and s40) had very low SDs. Geovisualizations did not identify any distinctive patterns that would help explain these differences across participants. The differences may have occurred because crime exposures are highly dependent on the unique geographic distribution of crime in the study area and the exposure measures obtained are not heavily influenced by the spatial configurations of the participants’ activity spaces. This in turn may be due to fact that contextual areas other than the GTP and GTB are relatively large polygons that cover many census tracts, attenuating the influence of extremes and thus producing similarly moderate estimates for crime exposure.

4.4. Factor analysis of the associations among the contextual variables

To assess the extent to which contextual variables derived with different contextual areas capture similar or different information regarding exposures, their associations were examined

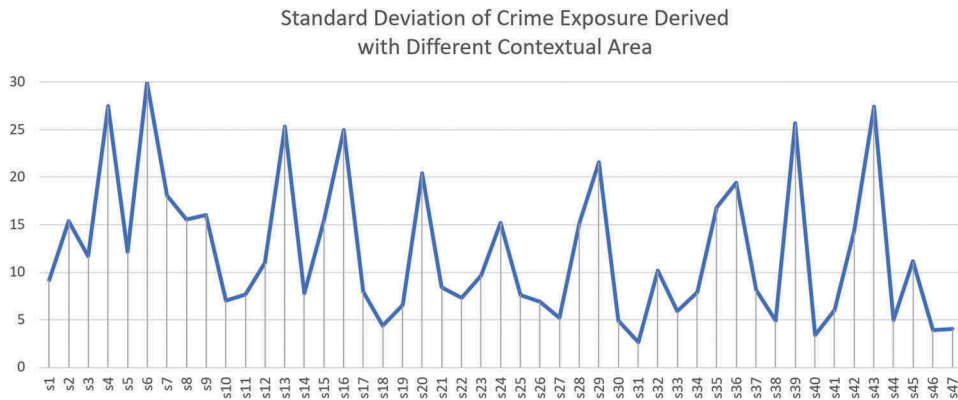


Figure 7. Standard deviation of crime exposures based on different contextual areas for the 47 participants.

Table 4. Factor loadings of CSI exposures based on different contextual areas.

	Factor loadings			Communalities
	Factor 1	Factor 2	Factor 3	
KDS	0.896	0.351	0.155	0.951
MCP	0.093	0.054	0.920	0.858
SDE1	0.580	0.743	0.083	0.896
SDE2	0.183	0.927	0.230	0.946
GTB	0.291	0.292	0.770	0.762
GTP	0.933	0.162	0.256	0.962
Variance explained	2.136	1.650	1.588	5.374
% of Variance	35.61	27.50	26.46	89.57

Note: Loadings over 0.7 are in bold type.

using factor analysis. Three factors were extracted from the six measures, and a varimax rotation was performed to make these factors more interpretable. These three rotated factors together explained 89.57% of the total variance for CSI exposures (Table 4) and 87.02% of the total variance for crime exposures (Table 5). It can be seen from these tables that all six exposure measures had large communalities, which indicate that a large amount of their variance has been extracted. Figures 8 and 9 visualize the factor loadings of the six measures with three-dimensional scatterplots, in which clusters of different types of exposure measures can be easily identified. As these figures show, KDS and GTP measures had high loadings (over 0.7) on Factor 1, on which SDE1 also had moderate loadings (over 0.5). Furthermore, SDE1 and

Table 5. Factor loadings of crime exposures based on different contextual areas.

	Factor loadings			Communalities
	Factor 1	Factor 2	Factor 3	
KDS	0.899	0.011	0.351	0.932
MCP	0.036	0.926	-0.048	0.861
SDE1	0.508	-0.012	0.698	0.745
SDE2	0.212	0.198	0.900	0.895
GTB	0.121	0.869	0.275	0.845
GTP	0.937	0.175	0.185	0.943
Variance explained	2.005	1.682	1.533	5.220
% of Variance	33.42	28.04	25.56	87.02

Note: Loadings over 0.7 are in bold type.

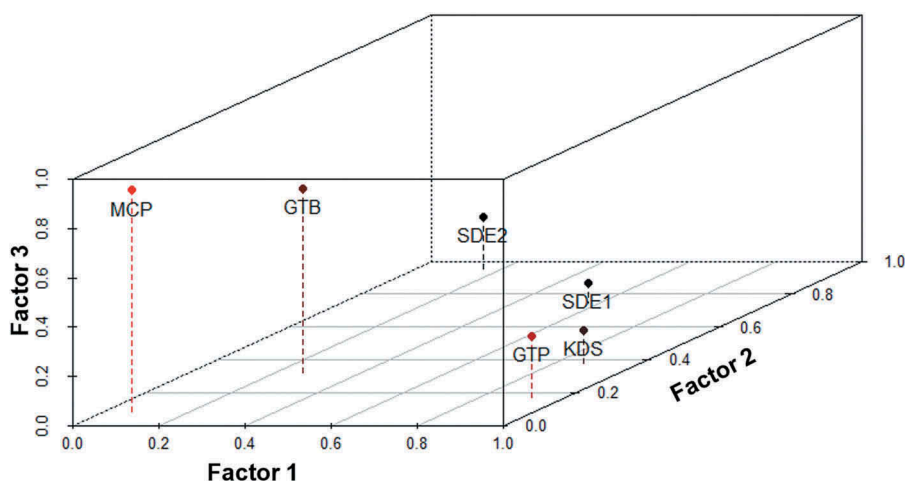


Figure 8. Factor loadings of CSI exposures based on different contextual areas on Factors 1, 2 and 3.

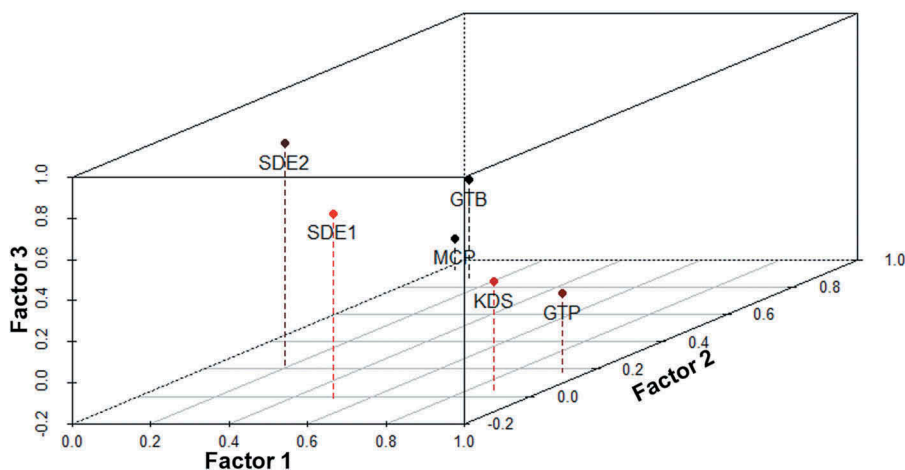


Figure 9. Factor loadings of crime exposures based on different contextual areas on Factors 1, 2 and 3.

SDE2 both had high loadings (over 0.7) on Factor 2, while MCP and GTB had high loadings (over 0.7) on Factor 3. As to the factor loadings for crime exposure, similar patterns were found. KDS and GTP measures had high loadings (over 0.7) on Factor 1, while MCP and GTB had high loadings (over 0.7) on Factor 2. In addition, only SDE2 had high loadings (over 0.7) on Factor 3, on which SDE1 also had moderate loadings (over 0.5). Overall, a general pattern can be identified: values of exposure measures obtained with KDS and GTP were similar, those obtained with SDE1 and SDE2 fell into another group and those obtained with MCP and GTB fell into a third group.

4.5. Regression analyses on CSI and crime estimates as predictors of substance use behavior

Multivariate linear regression models were used to examine the associations between the participants' exposure to psychosocial stress (based on the CSI and crime) and their substance use behaviors. Multilevel models were not feasible because there was no obvious spatial clustering in participants' home location and the number of participants was small. Further, given that the average GPS tracking period was only 107 days, both community SES and crime in the study area were assumed to be stable enough not to require longitudinal analyses.

The dependent variables were two measures of substance use for each participant: total and standardized. The total substance use score for each participant was the sum of seven substance use indicators based on urine tests performed three times each week during the study period. Each indicator reflects the presence or absence of amphetamine, barbiturates, benzodiazepines, opiates, cocaine, phencyclidine and cannabinoids (1 for presence and 0 for absence). Because the number of total urine tests differed among participants, a standardized substance use score for each participant was obtained by dividing the total score by the number of urine tests. Both substance use scores were log-transformed to minimize their skewness. The main independent variables in all regression models were the CSI and crime exposure measured by the seven contextual areas. There were thus 14 models: 7 used the total substance use score, and 7 used the standardized substance use score. Another 14 models included participants' demographic characteristics: gender, race, income, marital status and employment status. There were no significant associations among substance use, contextual exposures and demographic characteristics, and R^2 values of the regression models were uniformly low, ranging from 0.020 to 0.337.

However, the finding that exposures to CSI and crime were not significantly associated with substance use behavior does not necessarily mean that these contextual influences are unimportant. All participants were substance users admitted for methadone maintenance at a research clinic, and there was no control group of nonusers, so it is possible that participants' substance use behaviors were influenced more by the momentary psychosocial stress they experienced at particular places and times (e.g. sighting of law enforcement personnel at a particular time and place) than by the general sociogeographic contexts assessed using their activity spaces (Kwan 2018).

5. Conclusion

This study used a GPS dataset collected from substance users in Baltimore, Maryland, to explore how estimates of substance users' exposure to psychosocial stress may be affected by the contextual areas used to derive the exposure measures. It examined how geographic context defined and operationalized differently may lead to different exposure estimates and different conclusions about their effects on health, using two variables (a composite measure of community SES and crime) to assess participants' exposure to psychosocial stress. The study sought to shed light on the inconsistencies in previous findings and contribute to the nascent literature on the UGCoP in health and GIScience research.

The results indicate that different delineations of contextual areas yield different exposure estimates, and this may lead to different conclusions. For instance, values of CSI based on different contextual areas varied greatly, and variation among participants was largest with the HBs and the GTPs, and smallest with MCP and GTB. Six out of 15 pairs of CSI estimates were significantly different. With respect to crime, exposures assessed with KDS and GTP had the largest variations among the 47 participants, and exposures assessed with MCP had the least variation. Eleven out of 15 pairs of crime-exposure estimates were different from each other. These results suggest that contextual uncertainty is an important issue when examining the effects of various contextual factors on substance use behaviors. It has important implications for future research on the effect of contextual influences on health behaviors and outcomes: whether a study observes any significant influence of an environmental factor on health depends on what contextual units are used to assess individual exposure.

Several areas seem promising for future research. First, as pointed out earlier in this paper, participants' substance use behaviors may be influenced more by the momentary psychosocial stress they experienced at particular places and times than by the socio-geographic contexts assessed using their activity spaces (Kwan 2018). This may be an important basis for momentary interventions. Second, as our ongoing work indicates, whether a participant used a substance may be influenced by the sociogeographic context he/she experienced several hours ago; substance use may be a response to psychosocial stress with a certain time lag. Future studies should try to examine the particular temporality of the association between contextual influences and people's substance use behaviors. Lastly, individual response to the same contextual influences may be highly idiosyncratic (Kwan 2018). A substance user may feel stressed in places where nonusers typically feel safe (e.g. areas with high SES, or low-crime areas that are heavily patrolled by police). Future studies should try to take into account the idiosyncratic responses of individuals to the same contextual influences.

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ORCID

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

Jue Wang  <http://orcid.org/0000-0002-6305-4298>

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