Spatializing Area-Based Measures of Neighborhood Characteristics for Multilevel Regression Analyses: An Areal Median Filtering Approach

Masayoshi Oka and David W. S. Wong

ABSTRACT *Area-based measures of neighborhood characteristics simply derived from enumeration units (e.g., census tracts or block groups) ignore the potential of spatial spillover effects, and thus incorporating such measures into multilevel regression models may underestimate the neighborhood effects on health. To overcome this limitation, we describe the concept and method of areal median filtering to spatialize area-based measures of neighborhood characteristics for multilevel regression analyses. The areal median filtering approach provides a means to specify or formulate “neighborhoods” as meaningful geographic entities by removing enumeration unit boundaries as the absolute barriers and by pooling information from the neighboring enumeration units. This spatializing process takes into account for the potential of spatial spillover effects and also converts aspatial measures of neighborhood characteristics into spatial measures. From a conceptual and methodological standpoint, incorporating the derived spatial measures into multilevel regression analyses allows us to more accurately examine the relationships between neighborhood characteristics and health. To promote and set the stage for informative research in the future, we provide a few important conceptual and methodological remarks, and discuss possible applications, inherent limitations, and practical solutions for using the areal median filtering approach in the study of neighborhood effects on health.*

KEYWORDS *USA, Areal data, Area-based measures, Median filter, Multilevel regression analysis, Spatial approach, Spatial median*

INTRODUCTION

Several review articles have summarized a considerable amount of research conducted during the past two decades to understand the neighborhood effects on health.^{1–12} Throughout this paper, “previous studies” and “existing studies” generally refer to research articles summarized in these review articles. In previous studies,^{1–12} multilevel regression models^{13–16} have been used as a statistical tool to combine traditionally distinct individual-level and ecological analyses, and to avoid individualistic and ecological fallacies.¹⁷ Note that multilevel regression models are also known as hierarchical, mixed, mixed-effect, nested, or random-effect regression models in different fields of study. By separating the effects of contextual- and

Oka is with the Social and Cardiovascular Epidemiology Research Group, Faculty of Medicine, University of Alcalá, Campus Universitario - Ctra. Madrid-Barcelona, Km 33,6000, 28871, Alcalá de Henares, Madrid, Spain; Wong is with the Department of Geography and GeoInformation Science, College of Science, George Mason University, Fairfax, VA, USA.

Correspondence: Masayoshi Oka, Social and Cardiovascular Epidemiology Research Group, Faculty of Medicine, University of Alcalá, Campus Universitario - Ctra. Madrid-Barcelona, Km 33,6000, 28871, Alcalá de Henares, Madrid, Spain. (E-mail: moka@post.harvard.edu)

individual-level factors, previous studies¹⁻¹² have demonstrated the associations of neighborhood characteristics with various health behaviors and health outcomes after accounting for individual sociodemographic characteristics (e.g., age, gender, race/ethnicity, educational achievement, income level, employment status, and/or marital status). On the whole, both theoretical and empirical foundations of neighborhoods and health research offer a strong basis to suggest that “where we live” matters for our health over and above “who we are.”¹⁸

While a large number of studies have been conducted to date, the current state of knowledge about neighborhoods and their links to health is subject to several limitations.^{19,20} Notably, the vast majority of existing studies¹⁻¹² do not account for the potential of spatial spillover effects (or, more generally, the spatial relationships between geographic locations) in their multilevel regression analyses. Therefore, Diez Roux,^{19,20} Spielman and Yoo,²¹ and Perchoux et al.,²² have criticized that the neighborhood characteristics surrounding the residents are not adequately represented and analyzed in existing studies.¹⁻¹² Such a conceptual and methodological criticism primarily pertains to the definition of neighborhood boundary. In the United States (US), for example, census tracts (sometimes block groups or zip-code tabulation areas (ZCTAs)) have been routinely used to denote “neighborhoods” in previous studies.¹⁻¹² The use of census tracts has been favored in US studies due to two main reasons: (i) unlike block groups or ZCTAs, census tracts are relatively homogeneous with regard to population characteristics, economic status, and living conditions; they generally consist of about 4000 inhabitants,²³ and (ii) census tracts are a national creation of democratic governance informed by local inputs, are also delineated historically in accordance with uniform standards, and tend to be stable over time.²⁴ These desirable properties make census tracts reliable enumeration units for data aggregation by the US Census Bureau, and thus they have been widely used in US studies. For these reasons, using census tracts as neighborhoods is now considered as a standard practice in multilevel regression analyses.

Despite the desirable properties, census tracts (as well as block groups and ZCTAs) are artificial demarcations overlaid onto a geographic space. By and large, census tract boundaries follow visible and identifiable physical features (e.g., streets and rivers). The use of census tracts in neighborhoods and health research, therefore, assumes that residents’ activity space (i.e., the local area in which people move or travel) in their place of residence, and thus residents’ exposure to their residential environments take place only within such boundaries. However, neighborhoods are not confined to arbitrarily define enumeration unit boundaries; a meaningful specification or formulation of neighborhoods needs to embody the spatial nature of geographic locations.^{25,26} From a conceptual standpoint, using census tracts oversimplify residents’ daily mobility patterns in their place of residence.^{19,22} For instance, residents living near the edge of a census tract are likely to cross a street (which corresponds to the invisible boundary) and to be on the other side of the census tract on a daily basis. From a methodological standpoint, a misspecification of exposure to residential environments may produce unreliable or misleading results from a regression analysis.^{20,21} In particular, existing studies¹⁻¹² may have underestimated the neighborhood effects on health.²¹ Taken together, an unrealistic conceptualization of neighborhoods, and thus an inadequate statistical analysis of neighborhood characteristics in multilevel regression analyses would lead to incomplete (if not biased) knowledge about the role of neighborhood context in health (i.e., either an adverse, a protective, or a null effect).

In order to address some of these conceptual and methodological concerns,^{19–22} we describe the concept and method of areal median filtering to account for the potential of spatial spillover effects in multilevel regression analyses. We provide didactic examples both in conceptual and methodological ways. For demonstration purposes, we show how commonly used area-based measures of neighborhood affluence-deprivation and suburban-urban continua can be modified into spatial measures, and also demonstrate the differences between traditional and areal median filtering approaches. To promote and set the stage for informative research in the future, we provide a few important conceptual and methodological remarks, and also discuss possible applications, inherent limitations, and practical solutions. We use St. Louis, MO, as an example to demonstrate and illustrate these points.

QUANTIFYING NEIGHBORHOOD CHARACTERISTICS

Toward a more accurate examination of the neighborhood effects on health,^{19–22} spatial spillover effects are an important source of externality in quantifying neighborhood characteristics associated with demographic composition and physical condition. An inquiry into the importance or relevance of externality in the spatial patterns of human and physical phenomena dates back a few decades,^{27,28} and thus the notion of spatial spillover effects or spatial externalities is widely accepted as the pivotal component in the analysis of area, environment, place, and space.^{29,30} The underlying motivation for such spatial thinking is grounded in Tobler's first law of geography:³¹ "everything is related to everything else, but near things are more related than distant things" (p. 236). These, in turn, convey a spatial perspective that the characteristics of a neighborhood are not merely shaped by a particular bounded location, but are also shaped by the characteristics of its surrounding locations.

Moving beyond the traditional realm of city- and metropolitan-scale analysis,^{29,30} a number of studies have highlighted the role of spatial spillover effects in understanding the neighborhood effects on health. For example, Durlauf³² indicated that the ability of wealthier families to separate themselves from the low socioeconomic groups has led to the significant stratification of neighborhoods by income; wealthy families tend to live in an affluent neighborhood surrounded by similarly affluent neighborhoods, whereas poor families tend to live in a deprived neighborhood surrounded by equally deprived neighborhoods. He conceived spatial spillover effects to heighten the level of separation between the most affluent and most deprived neighborhoods. In a parallel realm of importance, Morenoff and Sampson³³ showed that high (or low) levels of homicide around a given neighborhood led to greater (or lesser) population losses; in their analysis, high levels of homicide and increases in the spatial proximity to homicide over time were significant predictors of such population changes. Another study by Sampson et al.³⁴ also showed that the levels of social capital and collective efficacy for children in a given neighborhood were linked to the relative spatial position of that neighborhood within the city; they noted children living in a given neighborhood benefited from (or harmed by) their proximities to neighborhoods with high (or low) levels of shared parental expectations for child social control. Building upon these theoretical and empirical foundations, Galster^{25,26} suggested that the potential of spatial spillover effects needs to be considered in quantifying neighborhood characteristics associated with demographic composition and physical condition.

To account for the potential of spatial spillover effects, for example, a binary weight³⁵ or a spatial kernel^{36,37} has been implemented into areal data. In brief, binary weight considers the spatial externalities of neighboring census tracts and gives equal weights to all neighboring census tracts, whereas spatial kernel considers the local intensity of the spatial externalities of all census tracts in a given area and gives more weights to census tracts located near than those farther away. Commonly considered in geographical research, spatial kernel captures the distance decay effect,^{38–42} which reflects the nature of spatial relationships that decline with increasing distances.³¹ However, it has long been emphasized that the form of geospatial data (i.e., areal or point-referenced data) and the (ir)regularity of geographic features determine the suitable approach in modeling spatial relationships.^{43,44} In fact, spatial kernels and associated distance-decay parameters are strongly influenced by the spatial structure, including the size and the geometric configuration of areal data.^{45–48} Specifically, spatial kernels are suited for modeling equally spaced grid-like patterns where the rate of distance decay is uniform across geographic space. In handling areal data, it is important to recall that the rate of distance decay between census tracts (as well as block groups and ZCTAs) is not uniform because the size of census tracts increases from urban to rural areas in relation to the density of settlement. As a result, spatial kernels tend to underestimate or even ignore the spatial relationships of irregular census tracts with varying spatial extents.

In addition to the computational difficulties associated with implementing a spatial kernel into areal data,^{45–48} a binary weight is not as ill-suited as long been concerned by different authors.^{36,37} Particularly for US studies, it can reasonably take into account for the potential of spatial spillover effects in urban settings. For example, recent studies conducted in three different regions of the US showed that the local area of participants' daily mobility overlapped with their census tract of residence and its neighboring census tracts.^{49–51} Moreover, two studies conducted in different US cities showed that resident-defined neighborhood boundaries were very close to the size of a census tract (in terms of land area), but typically included portions of at least one neighboring census tract (rather than a complete single census tract),⁵² and that resident-defined neighborhood boundaries contained their census tract of residence and its neighboring census tracts.⁵³ Given the diverse settings in which these five US studies were conducted, these findings substantiate the value to the desirable properties of census tracts.^{23,24} Put differently, when a census tract is used to denote a neighborhood, it may be adequate for quantifying the neighborhood characteristics of residents living at or near the center of the census tract, but may not be for those living near the border or edge of the census tract. Therefore, to account for the potential of spatial spillover effects, area-based measures of neighborhood characteristics need to consider not only the census tract of residence but also its neighboring census tracts.^{49–53}

To summarize, neighborhoods may be viewed as the local areas corresponding to residents' activity spaces.^{54,55} Recent US studies in urban settings^{49–53} corroborate the idea that the census tract of residence and its neighboring census tracts can be used in this regard. Therefore, using a binary weighting scheme to define the memberships of neighboring census tracts is preferred over the spatial kernel scheme. By accounting for the potential of spatial spillover effects, incorporating the derived area-based measures of neighborhood characteristics into multilevel regression analyses addresses some of the conceptual and methodological concerns raised by Diez Roux,^{19,20} Spielman and Yoo,²¹ and Perchoux et al.²² Hence, an integration of spatial thinking into multilevel thinking will allow us to more accurately examine the neighborhood effects on health.

MATERIALS AND METHODS

Data

Area-based sociodemographic data at the census tract level were obtained from the 2005–2009 American Community Survey (ACS) for St. Louis, MO (St. Charles County, St. Louis County, and St. Louis City). Note that the 5-year ACS estimates are based on a larger sample size and thus more reliable than the 1- and 3-year estimates. The 2000 US census tract boundary shapefile was obtained from the US Census Bureau. Since census tract boundaries extend into rivers and/or include large ponds and lakes, such water bodies were removed from the boundary shapefile when the total land area (in square kilometers) was recalculated in GIS (ArcGIS 10.2; ESRI Inc., Redlands, CA, USA). This recalculation procedure better represents the actual land surface area in which people move or travel. A shapefile of water bodies was obtained from the Data & Maps Collection for ArcGIS on DVD, and all shapefiles were projected using the NAD 1983, State Plane Coordinate System.

Areal Median Filtering Approach

When census tract boundaries are simply used to denote neighborhoods, each census tract is treated as an “island” because information about the spatial relationships between census tracts is not considered. By design, area-based measures of neighborhood characteristics simply derived from such boundaries are aspatial in nature. Hereafter, “aspatial” refers to the insensitivity of analytical results to the spatial arrangement of enumeration units (e.g., census tracts or block groups). Rather than relying solely on census tract boundaries, a better approach is to remove those boundaries as the absolute barriers and to incorporate information about the spatial relationships between census tracts. This “spatializing” process converts aspatial measures of neighborhood characteristics into spatial measures.

To derive a spatial measure of neighborhood characteristics, Wong³⁵ introduced the concept of composite population to more realistically portray the experience of residents living in a given census tract by accounting for the spatial interaction (i.e., the movement of people across geographic space) across neighboring census tracts. Adopting the concepts in modeling spatial autocorrelation,^{56,57} he suggested using the function $c_{ij}(\cdot)$ to remove the census tract boundaries as the absolute barriers for spatial interaction.³⁵ Let census tract i be the reference unit, $c_{ij}(\cdot)$ is the element of a modified binary (0, 1) connectivity matrix where (i) $c_{ij}=1$ indicates that census tracts i and j are neighbors, and $c_{ij}=0$ otherwise, and (ii) i can equal to j and thus $c_{ii}=1$. By implementing the function $c_{ij}(\cdot)$, for example, the composite population count of group G in census tract i (cg_i) is modeled as

$$cg_i = \sum_j c_{ij}g_j$$

where g_j is the population count of group G in census tract j . Therefore, cg_i is the sum of the population count in census tract i plus the population counts in its neighboring census tracts j . This specification implicitly accounts for the spatial interaction of residents across census tracts.

Wong’s approach³⁵ provides a more realistic representation of residents’ activity space^{49–53} than the traditional approach that relies solely on a single census tract. However, the concept of composite population³⁵ was designed to handle only discrete variables (i.e., population counts), and thus cannot handle continuous

variables (e.g., median household income and income-to-poverty ratio). As a possible way to handle continuous variables, the concept of composite population³⁵ can be modified by integrating the concept of median filter (also referred to as moving medians).⁵⁸ We define the integration of these two concepts as the concept of areal median filtering. Note that the median is a more robust measure of central tendency than the mean when the data are skewed. Therefore, the role of median filter in the areal median filtering approach is to measure a central tendency of neighborhood characteristics.

In handling continuous variables, the areal median filtered measure of census tract i (mq_i) is modeled as

$$mq_i = median\{c_{ij}q_j\}$$

where q_j is the interval or ratio measure of census tract j . Therefore, mq_i is the median of the interval or ratio measure of census tract i and its neighboring census tracts j . This specification implicitly removes census tract boundaries as the absolute barriers and also pools information from neighboring census tracts to quantify a representative description of neighborhood characteristics surrounding the residents living in census tract i . Figure 1 illustrates the difference between traditional and areal median filtering approaches in quantifying the interval or ratio measure of neighborhood characteristics.

Among previous studies,^{1–12} neighborhood characteristics along the affluence-deprivation and suburban-urban continua were two common area-based measures used in neighborhoods and health research. The areal median filtering approach can be used to convert aspatial measures of these two neighborhood characteristics into spatial measures.

First, the aspatial measure of neighborhood deprivation (M_i , also known as the measure of material deprivation), which captures the affluence-deprivation continuum, is defined as

$$M_i = f^{-1}(h_i) \tag{1}$$

FIG. 1 Illustration of the difference between traditional and areal median filtering approaches. The function c_{ij} ³⁵ is used to remove the enumeration unit boundaries as the absolute barriers for spatial interaction, and the median filter⁵⁸ is used to measure a central tendency of neighborhood characteristics. The areal median filtering approach is designed to handle continuous variables (i.e., interval or ratio measures). This spatializing process addresses some of the conceptual and methodological concerns raised by different authors.^{19–22}

where h_i is the median household income (US \$) in census tract i and $f^{-1}(\cdot)$ is the inverse function. Here, median household income was used because Oka⁵⁹ showed that it was highly, but negatively correlated ($-0.85 \leq r \leq -0.92$) with area-based composite measures of socioeconomic position (SEP),⁶⁰ socioeconomic deprivation (SED),⁶¹ and deprivation (DEP)⁶² in St. Louis, MO. Note that SEP, SED, and DEP are comprised of 6, 17, and 8 area-based socioeconomic variables, respectively. Although median household income was also highly and positively correlated with median family income ($r=0.94$), median household income had less missing data than median family income. Since the increase in median household income refers to the increase in neighborhood affluence, its inverse correspondingly refers to the increase in neighborhood deprivation.⁵⁹ Based on the areal median filtering approach, the spatial measure of neighborhood deprivation (SM_i) is defined as

$$SM_i = f^{-1}(mh_i) \quad (2)$$

where mh_i is the median of the median household income in census tract i and its neighboring census tracts j .

Second, the aspatial measure of neighborhood urbanness (U_i), which captures the suburban-urban or rural-suburban-urban continuum, is defined as

$$U_i = d_i \quad (3)$$

where d_i is the population density (the number of total population divided by the size of land area in square kilometers) in census tract i . Based on the areal median filtering approach, the spatial measure of neighborhood urbanness (SU_i) is defined as

$$SU_i = md_i \quad (4)$$

where md_i is the median of the population density in census tract i and its neighboring census tracts j .

Using census tracts as the basic enumeration units, aspatial and spatial measures of neighborhood deprivation (M_i and SM_i , respectively) and neighborhood urbanness (U_i and SU_i , respectively) were computed in R.^{63,64} As defined above, the function $c_{ij}(\cdot)$ implemented in SM_i and SU_i is a list of polygon neighbors that includes the census tract itself (i.e., $c_{ii}=1$) and census tracts sharing a common boundary with or touching a boundary of census tract i (i.e., $c_{ij}=1$). Then, the median is calculated to derive the areal median-filtered measures (see Fig. 1) after excluding census tracts that do not share or touch a boundary (i.e., $c_{ij}=0$). The R codes for computing SM_i and SU_i are given below:

```
library(spdep)
# The function  $c_{ij}(\cdot)$ 
c_ij = nb2mat(include.self(poly2nb(Data, queen = TRUE)), style = "B", zero.policy = TRUE)
# Replacing 0 s with NAs
c_ij[c_ij==0] = NA
# Spatial Measure of Neighborhood Deprivation
Median_Household_Income_c_ij = mapply("c_ij", Median_Household_Income, SIMPLIFY = TRUE)
Median_Household_Income_c_ij_matrix = matrix(Median_Household_Income_c_ij, nrow = nrow(c_ij), ncol = nrow(c_ij), byrow = TRUE)
SM = (-1)*apply(Median_Household_Income_c_ij_matrix, 1, FUN = "median", na.rm = TRUE)
```

```
# Spatial Measure of Neighborhood Urbanness
Population_Density_c_ij = mapply("c_ij", Population_Density, SIMPLIFY = TRUE)
Population_Density_c_ij_matrix = matrix(Population_Density_c_ij, nrow = nrow(c_ij),
ncol = ncol(c_ij), byrow = TRUE)
SU = apply(Population_Density_c_ij_matrix, 1, FUN = "median", na.rm = TRUE)
Note that the inverse function  $f^{-1}(\cdot)$  in  $M_i$  and  $SM_i$  is multiplying area-based
measures by  $-1$  (negative one).
```

Analysis

To demonstrate the differences between aspatial and spatial measures of neighborhood deprivation and neighborhood urbanness, scatterplots and Pearson product-moment correlation coefficients (r) were computed in R⁶⁵ for St. Louis, MO (Fig. 2). As a supplemental illustration, histograms of these aspatial and spatial measures are shown in the lower panels of Fig. 2. For visual analysis, the geographical distributions of area-based measures derived from M_i , SM_i , U_i , and SU_i were mapped in GIS for St. Louis, MO (Fig. 3). For interpretation purposes, these four area-based measures were normalized to their range, such that all measures are bounded between 0 and 1. Here, the purpose of rescaling aspatial and spatial measures is to provide an interpretable comparison of the changes from low to high values in a consistent manner. These normalizations are justifiable as the purpose of comparing aspatial and spatial measures is to capture within-city variations, not between-city differences. A quantile classification scheme was used to display the levels of neighborhood deprivation and neighborhood urbanness.

FIG. 2 Relationships between aspatial and spatial measures of neighborhood characteristics in St. Louis, MO (340 census tracts). **a** area-based measures of neighborhood deprivation and **b** area-based measures of neighborhood urbanness. The *upper panels* show scatterplots and Pearson product-moment correlation coefficients (r) between aspatial and spatial measures, and the *lower panels* show histograms of those measures.

FIG. 3 Geographic distributions of aspatial and spatial measures of neighborhood characteristics in St. Louis, MO (340 census tracts). **a** aspatial measure of neighborhood deprivation, **b** spatial measure of neighborhood deprivation, **c** aspatial measure of neighborhood urbanness, and **d** spatial measure of neighborhood urbanness.

The normalization process retains rank order and the relative degree of separation between area-based measures within a given study area. However, the degree of separation between affluent and deprivation neighborhoods and the intensity of settlements vary from city to city. In other words, the highest and lowest values of median household income and population density in St. Louis, MO are unlikely to be the highest and lowest values, for example, in New York, NY, Los Angeles, CA, Chicago, IL, Houston, TX, and Philadelphia, PA. Therefore, the absolute area-based measures should be used when the purpose of comparing aspatial and spatial measures is to capture between-city differences.

To quantitatively demonstrate the difference between aspatial and spatial measures (i.e., M_i and U_i versus SM_i and SU_i) in the context of multilevel regression analysis, we constructed a hypothetical data of 3000 individuals living across 300 census tracts in St. Louis, MO (Table 1). As an example, we use obesity as the outcome of interest: non-obese versus obese. By incorporating neighborhood- and

TABLE 1 Description of a hypothetical data in St. Louis, MO (3000 individuals living across 300 census tracts)

Individual-level outcome		
Non-obese	BMI <30	70.0 %
Obese	BMI ≥30	30.0 %
Individual-level sociodemographics		
Age	Minimum	25.0
	Mean	39.2
	Median	39.0
	Maximum	65.0
Gender	Female	50.0 %
	Male	50.0 %
Education	≥16 years	25.1 %
	13–15 years	25.1 %
	12 years	32.9 %
	<12 years	11.9 %
	NA	5.0 %
Income	≥\$100,000	15.1 %
	\$75,000–\$99,999	15.8 %
	\$50,000–\$74,999	18.4 %
	\$25,000–\$49,999	28.7 %
	<\$25,000	15.0 %
	NA	7.1 %

BMI body mass index, NA not available

individual-level covariates, two multilevel logistic regression analyses were carried out in R^{66,67} for St. Louis, MO (Table 2).

RESULTS

Figure 2 shows the correlations between aspatial and spatial measures of neighborhood deprivation and neighborhood urbanness. Comparing the aspatial and spatial measures of neighborhood deprivation (upper scatterplot in Fig. 2a), M_i is highly and positively correlated with SM_i ($r=0.90$). Similarly, comparing the aspatial and spatial measures of neighborhood urbanness (upper scatterplot in Fig. 2b), U_i is highly and positively correlated with SU_i ($r=0.83$). While scatterplots display linear associations between these aspatial and spatial measures, clear discrepancies can be observed among the varying levels of neighborhood deprivation and neighborhood urbanness measures. These discrepancies are attributable to the skewness of those measures where M_i and SM_i are negatively skewed, whereas U_i and SU_i are positively skewed (lower histograms in Fig. 2).

For visual assessment of the difference between traditional and areal median filtering approaches, the spatial arrangements of aspatial and spatial measures of neighborhood deprivation and neighborhood urbanness are shown in Fig. 3. By comparing the geographical distributions of M_i and SM_i (Fig. 3a versus Fig. 3b) as well as U_i and SU_i (Fig. 3c versus Fig. 3d), it is clear that aspatial measures and its spatial counterparts do not exactly resemble the same spatial patterns; noticeably, SM_i and SU_i show much “smoother” spatial patterns than M_i and U_i , respectively. The “smoothness” of spatial measures and thus the dissimilar spatial patterns

TABLE 2 Hypothetical multilevel logistic regression analysis of obesity in St. Louis, MO

		Model 1	Model 2
Fixed effects		OR (95 % CI)	OR (95 % CI)
Neighborhood-level covariates			
Neighborhood deprivation (M_i)		1.20 (1.13, 1.28)	
Neighborhood urbanness (U_i)		0.54 (0.26, 1.11)	
Neighborhood deprivation (SM_i)			1.24 (1.15, 1.33)
Neighborhood urbanness (SU_i)			0.44 (0.20, 0.95)
Individual-level covariates			
Age		1.05 (1.04, 1.06)	1.05 (1.04, 1.06)
Gender	Female	Ref.	Ref.
	Male	0.50 (0.42, 0.61)	0.51 (0.42, 0.61)
Education	≥16 years	Ref.	Ref.
	13–15 years	1.25 (0.94, 1.66)	1.26 (0.95, 1.68)
	12 years	1.59 (1.22, 2.09)	1.61 (1.23, 2.11)
	<12 years	1.58 (1.11, 2.24)	1.59 (1.12, 2.25)
	NA	1.65 (0.85, 3.19)	1.62 (0.84, 3.13)
Income	≥\$100,000	Ref.	Ref.
	\$75,000–\$99,999	1.06 (0.75, 1.51)	1.08 (0.76, 1.54)
	\$50,000–\$74,999	1.10 (0.78, 1.55)	1.12 (0.80, 1.58)
	\$25,000–\$49,999	1.34 (0.96, 1.86)	1.38 (0.99, 1.92)
	<\$25,000	1.60 (1.10, 2.33)	1.63 (1.12, 2.37)
	NA	0.90 (0.50, 1.62)	0.93 (0.52, 1.67)
Random effects		Variance (SE)	Variance (SE)
Census tract		0.477 (0.690)	0.478 (0.691)
Goodness-of-fit measures			
Akaike information criterion (AIC)		3278.327	3281.703
Bayesian information criterion (BIC)		3368.423	3371.798
Log-likelihood		−1624.164	−1625.851
Deviance		3248.327	3251.703

OR odds ratio, CI confidence interval, NA not available, Ref. reference category, SE standard error

compared with its aspatial counterparts is attributable to the potential of spatial spillover effects^{27–30} in areal data. These, in turn, illustrate the importance of a spatial perspective that area-based measures of neighborhood characteristics are not merely shaped by a particular bounded census tract, but are also shaped by its neighboring census tracts.

The areal median filtering approach, which smooths the areal data spatially, is helpful not only for the visualization of spatial patterns, but also for the detection of spatial clusters.⁶⁸ For example, highly deprived neighborhoods clustered in the eastern parts of the city in Fig. 3a are much more recognizable in Fig. 3b because those neighborhoods are adjacent to and/or surrounded by equally high levels of neighborhood deprivation. In a similar fashion, densely populated neighborhoods clustered in the eastern, northern, and southeastern parts of the city in Fig. 3c are much more profound in Fig. 3d since those neighborhoods are adjacent to and/or surrounded by similarly high levels of neighborhood urbanness. These “smoothed” maps can serve as the foundations for exploratory spatial data analysis (ESDA)^{69–71} to synthesize knowledge gained from existing and future studies toward informing public policies and decision-making. As a potential contribution, the visualization of high-risk neighborhood clusters through ESDA can assist health researchers and

their collaborators in identifying where the resources should be allocated for designing effective community-based interventions or health promotions.

As a way to demonstrate the difference between traditional and areal median filtering approaches in the context of multilevel regression analysis, the associations of aspatial and spatial measures of neighborhood deprivation and neighborhood urbanness with obesity are shown in Table 2. Note that the parameter estimates are based on a hypothetical data of obesity described in Table 1, and thus they must not be considered as empirical evidence. Nevertheless, results from the two multilevel regression analyses (model 1 versus model 2) highlight the importance of using spatial measures of neighborhood deprivation (SM_i) and neighborhood urbanness (SU_i) over its aspatial counterparts (M_i and U_i , respectively). That is, the aspatial measure of neighborhood urbanness (U_i) is not associated with obesity in model 1 (OR 0.54, 95 % CI 0.26–1.11), but the spatial measure of neighborhood urbanness (SU_i) is associated with obesity in model 2 (OR 0.44, 95 % CI 0.20–0.95). Otherwise, changes in the estimation of other fixed effects, random effects, and goodness-of-fit measures are negligible. These suggest that a multilevel regression analysis based on the aspatial measures may underestimate the potential risk of obesity among people living in suburban neighborhoods. Rooted in the core concepts of spatial thinking,^{27–34} a comparison of model 1 with model 2 in Table 2 underscores the notion that spatial spillover effects are an important source of externality in the study of neighborhood effects on health.

When incorporating the areal median filtering approach into multilevel regression analyses, however, some caution is required in future studies. For instance, the association of SU_i with obesity in model 2 was conditional on SM_i (i.e., SU_i was not associated with obesity in a multilevel logistic regression analysis without SM_i). Therefore, the covariate inclusion and exclusion criteria should be based on theoretical and scientific insights, rather than the statistical significance in a preliminary analysis. In like manner, spatial spillover effects may have a lesser or greater relevance in a multilevel regression analysis depending on the outcome of interest (e.g., health behaviors versus health outcomes). To better understand the role of spatial spillover effects in neighborhoods and health research, a series of empirical studies are needed for various types of health indicators in different cities (e.g., sparse and dense urban settings) and regions (e.g., Eastern and Western states) across the USA.

From an analytical standpoint, the generalizability and transferability of empirical findings to different populations, geographic settings, contexts, and/or points in time are essential components in health research. Yet, the study of neighborhood effects on health is heavily influenced by how it is studied and how results are interpreted; the results obtained from a multilevel regression analysis can be contingent on what was considered (or was not considered) in the model. Hence, model building and the interpretation of results should be handled with care.

DISCUSSION

A realistic representation of neighborhood characteristics is needed for multilevel regression analyses; otherwise, only limited (if not biased) knowledge can be gained through existing and future studies.^{19–22} By integrating the concepts of composite population³⁵ and median filter,⁵⁸ we therefore described the areal median filtering approach to account for the potential of spatial spillover effects in quantifying a representative description of neighborhood characteristics surrounding the residents

living in a given census tract. This spatializing process allows us to specify or formulate neighborhoods as meaningful geographic entities in multilevel regression analyses. Notwithstanding the usefulness of the areal median filtering approach, there are arguably comparable, but slightly different, perspectives toward the integration of spatial smoothers (i.e., median filter versus mean filter) and the choice of enumeration units (i.e., census tracts versus block groups) that may arise in future studies. Hence, we discuss our point of view on these matters.

Regarding the spatial smoother, mean filter (also referred to as moving mean or moving average)^{72,73} may be used to introduce the areal mean filtering approach. This alternative approach simply replaces the median filter with the mean filter, and thus can be used to derive, for example, SM_i^* and SU_i^* . Borrowing the concept from time-series analysis, Curry⁷² discussed possible uses of mean filter for geospatial data, and Haining⁷³ provided a detailed theoretical treatment of using mean filter in modeling spatial interactions. By and large, both the concepts of mean and median filter, as well as other types of spatial smoothers, have been implemented in various modeling techniques.^{74–81} However, the use of median filter has long been advocated by Tukey⁵⁸ as a measure of central tendency. More importantly, the nature of local variability in a given region^{69–71} needs to be considered when choosing between the two filters. On one hand, mean filter tends to lessen unusual values in the data, and thus may be more suitable for handling geospatial data where localized outliers are generally not expected. On the other hand, median filter tends to preserve unusual values in the data, and thus may be more appropriate for handling geospatial data where localized outliers are expected. Taking these into consideration and potential applications in future studies, the areal median filtering approach is preferred over its alternative areal mean filtering approach.

With regard to the geographic unit of analysis, block groups (or its equivalent enumeration units) may be used when using census tracts deemed inappropriate or impractical in certain settings. For example, the size of census tracts becomes much larger in rural areas. Unfortunately, recent US studies on residential activity spaces have been conducted in urban settings.^{49–53} While little is known about the urban-suburban-rural differences in residential activity spaces, it is likely that block groups (instead of census tracts) may be well-suited to represent residents' activity space in their place of residence, and thus residents' exposure to their residential environments in rural settings. In such a case, the areal median filtering approach can be implemented into block groups (but following the same specification given above). Another possible scenario for using block groups is that enumeration units equivalent to the US census tracts may not exist in some countries. For instance, census sections (which are analogous to block groups in the US) have been used to denote neighborhoods in Spanish studies.^{82–87} If block groups were used in urban settings outside the USA, however, the function $c_{ij}(\cdot)$ should be modified to include higher-order (e.g., the second-, third-, or fourth-order) units. The inclusion of higher-order enumeration units is to compensate for the smaller area of block groups, which may not reasonably represent the extent of residents' daily mobility in their place of residence. The modified version of $c_{ij}(\cdot)$ can be denoted as $c_{ij}'(\cdot)$ to model mq_i' (similar to the specification given above).

While further efforts may focus on the use of other spatial smoothers and/or smaller enumeration units, the underlying principle remains the same. The key importance is that enumeration unit boundaries may not delimit residents' daily mobility patterns in their place of residence, and thus residents' exposure to their residential environments. As Getis⁸⁸ emphasized, prediction is imperative for

understanding the movement of people between places, not the degree of spatial autocorrelation present in a geospatial data or the statistical significance in a (multilevel) regression analysis. To this end, the areal median filtering approach provides a means to specify or formulate neighborhoods as meaningful geographic entities by removing the census tract boundaries as the absolute barriers and by pooling information from the neighboring census tracts to more realistically represent the characteristics of a neighborhood. These specifications or formulations address some of the conceptual and methodological concerns raised by different authors.^{19–22} Hence, the integration of mean filter (instead of median filter) and/or the use of block groups (instead of census tracts) can be viewed as an extension of, which may not be superior to, the areal median filtering approach.

As a technical note, we list a few words of caution for using the areal median filtering approach in future studies. First, an implementation of spatial function (binary weight³⁵ and spatial kernel^{36,37} alike) will be subject to the boundary or edge effect. Such an effect introduces bias into the identification of spatial distribution and the parameter estimates of spatial processes.⁸⁹ Since areal associations and geographic distributions extend beyond the demarcated boundary (e.g., county boundary), when the study area is “cropped” or “lifted” from its surrounding geography in the analysis, the measures or statistics computed within the study area would be biased. In particular, census tracts closer to the border of the study area will be affected more than those closer to the center of the study area. Several solutions have been proposed during the past decades, but none of them can fully solve the problem.^{90,91} Because the function $c_{ij}(\cdot)$ implemented in the areal median filtering approach involves only the first-order adjacency relation (Fig. 1), a buffer zone including census tracts immediately outside the study area will be sufficient for accounting the boundary or edge effect. If the function $c_{ij}'(\cdot)$ was to be used in rural areas of the USA or in non-USA settings, then the buffer size should be adjusted to include higher-order adjacency relations outside the study area.

Second, an implementation of spatial function (binary weight³⁵ and spatial kernel^{36,37} alike) smooths the spatial distribution of area-based measures. As shown in Fig. 3, it leads to a better visualization and detection of the systematic spatial patterns and spatial clusters within the study area. However, implementing a spatial function also magnifies the level of spatial autocorrelation (i.e., residuals that vary systematically over space), which in turn violate the assumption of independence. The violation of independence yield inflated R-square values, deflated standard errors, and overestimated t tests in the regression analysis.^{92,93} Because commonly used multilevel regression models only account for the within-group dependency, but not the between-group dependency,^{13–16} spatial autocorrelation between area-based measures of neighborhood characteristics (aspatial and spatial measures alike) must be handled in the multilevel regression analysis. One possible solution is to use (Bayesian) generalized geosadditive mixed models (GGAMMs),⁹⁴ which can be considered as a multilevel version of (Bayesian) generalized geosadditive models. Given the complexity of such statistical models, however, the use of GGAMMs, particularly when using Bayesian GGAMMs, is only recommended for those who have a clear comprehension of handling the multilevel and spatial data structures.

Third, an application of areal median filtering approach for measuring other types of neighborhood characteristics may face challenges due to the quality of ACS data. After the 2000 decennial census, the US Census no longer gathers detailed information on household's socioeconomic status and living conditions through the so-called long form. Replacing the long form is the ACS, which is an ongoing survey

conducted by the US Census Bureau since 2005 and remains the major source of socioeconomic and housing data. However, due to the changes made in the ACS,⁹⁵ estimates for smaller geographical units (e.g., census tracts, but more so for block groups) are not as reliable (with relatively large margin of errors) as the past decennial censuses. The inaccuracy of ACS data is primarily due to the reliance on small samples, particularly in sparsely population areas.^{96,97} Therefore, ACS data must be handled with care.

CONCLUSION

The study of neighborhood effects on health requires a spatial and multilevel thinking. In the context of neighborhoods and health research,¹⁸ the use of multilevel regression models has become the standard statistical approach during the past two decades.¹⁻¹² However, spatial thinking²⁷⁻³⁰ has been largely overlooked in existing studies.¹⁻¹² Only a limited number of studies have been conducted to account for the potential of spatial spillover effects in their multilevel regression analyses.⁹⁸⁻¹⁰² These five studies used local spatial segregation measures based on the concept of composite population.^{103,104} The dearth of spatial thinking is linked to the fact that no spatial measures, similar to the local spatial segregation measures, exist today to quantify other types and/or dimensions of neighborhood characteristics. The areal median filtering approach provides a means to fill the gap by spatializing area-based measures of neighborhood characteristics for multilevel regression analyses. Hence, the concept and method described in this paper contribute to the integration of spatial thinking into the already evident multilevel thinking in neighborhoods and health research.

The areal median filtering approach is designed to quantify continuous variables (i.e., interval or ratio measures), and thus we focused on deriving spatial measures of neighborhood deprivation (SM_i) and neighborhood urbanness (SU_i). If a discrete variable (i.e., population count) is of interest, then the composite population approach³⁵ should be considered instead. For example, residential segregation has long been considered to shape health in the USA¹⁰⁵⁻¹⁰⁸ and has become an increasing concern in Europe.¹⁰⁹ Because simple percentages (e.g., percent non-Hispanic black) cannot capture the spatial nature of segregation,^{110,111} we recommend using spatial measures of residential segregation developed by Wong.^{103,104} See Oka and Wong^{110,111} for helpful theoretical and methodological discussions on the measurement of residential segregation and for a useful critique on the misuse of ineffective and insufficient segregation measures. Capitalizing on the shared principle of using the function $c_{ij}(\cdot)$, the composite population and areal median filtering approaches can be used to handle discrete and continuous variables, respectively.

Besides spatial measures of neighborhood deprivation (SM_i) and neighborhood urbanness (SU_i) considered in this paper, the areal median filtering approach can be applied to capture various types of neighborhood characteristics for multilevel regression analyses. However, it is important to recognize that we provided the concept and method for areal data, and not for point-referenced data. In some instances, retail store densities (e.g., convenience stores, grocery stores, supermarkets, and tobacco stores) have been used to characterize the neighborhood physical (or built) environments. Widely recognized as a "malpractice" in handling geospatial data, aggregating point-reference data into census tracts (as well as any other enumeration units) would lead to the creation of artificial spatial patterns, a

source of bias known as the modifiable areal unit problem.¹¹² In order to foster informative research, we do not recommend the use of areal median filtering approach to combine two different types of geospatial data (i.e., areal and point-referenced data).

The use of multilevel regression models is one way to examine how spatial, sociocultural, institutional, and national contexts (e.g., neighborhoods, peers, families, religions, schools, workplaces, cities or metropolis, regions, and countries) may shape the health of individuals within them.^{113–116} While spatial regression models^{117–121} may be used to account for the potential of spatial spillover effects in neighborhoods and health research, they are not designed to handle multilevel data structures and thus cannot adequately analyze multiple contexts. Since the areal median filtering approach addresses some of the limitations inherent in multilevel regression analyses,^{19–22} future studies should focus not only on individual- and neighborhood-level factors (i.e., a simple two-level model), but also on factors operating at different contexts (i.e., a cross-classified model). Toward gaining a more well-rounded insight into the “web of causation,”¹²² the continued uses of multilevel regression models,^{13–16} more preferably the uses of GGAMMs,⁹⁴ provide a fruitful research paradigm for better understanding how micro-, meso-, and macro-level factors shape health.

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