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Built Environment and Behavior: Spatial Sampling Using Parcel Data

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Purpose

The quality and economy of inferential research rely heavily on the sampling method. This paper addresses a methodological challenge in environment-behavior research: sampling respondents in relation to their built environmental characteristics.

Methods

A discussion of issues related to traditional neighborhood-based sampling serves to introduce a new spatial sampling strategy. Spatial sampling consists of defining conceptual population of interest, constructing spatial sample frame using parcel-level environmental data in GIS, examining the sample frame, determining the sampling design and size, and drawing the samples. An application of this method is illustrated using a recent study examining environmental correlates of walking and biking.

Results

Spatial sampling with parcel-level data ensures sufficient variations in and proper distributions of the environmental variables of interest, while controlling for the conditions of no interest. The use of the individual as unit of analysis offers an economic, generalizable, and easily interpretable approach to environment-behavior research, and discourages the potentially erroneous a priori definition of neighborhoods and aggregation problems.

Conclusions

With its capacity to consider a broad range of detailed environmental variables, spatial sampling contributes to finding new or stronger environment-behavior associations and to the growing number of studies using the social ecologic model.

Key words: Sampling Studies; Environment; Health Behavior; Environment and Public Health; Geographic Information Systems

Article Outline

Background

Empirical research on the relationships between human behavior and physical environments must involve an equally careful treatment of both behavioral and environmental dimensions. Advances in the measurement of the built environment have lagged behind that of behavioral and sociodemographic attributes, due to insufficient data availability and cost-prohibitive field-data collection. In the past, physical environmental attributes have been measured at an aggregate level (census block group and larger) and characterized by overly simplified proxies (1). These constraints, coupled with the inability to computationally process large amounts of spatially referenced data, have contributed to a dearth of environmental behavior research since the 1980s 2 and 3.

Recent developments promise to move forward quantitative analyses of the built environment. First, the development of geographic information system (GIS) software has led to considerable investment in new environmental data collection by many local jurisdictions (4). Second, a new research direction in using social ecological approaches to addressing eminent public health issues, namely, increases in obesity and physical inactivity 5 and 6, recognizes the role of physical environment in shaping health behaviors 7 and 8. It involves extensive primary data collection for both behavioral and objective physical environmental variables 9, 10, 11, 12 and 13.

Objectives

The cost and quality of inferential research depend on the sampling strategy. However, commonly used sampling methods so far have largely failed to properly account for the physical environmental variables. This article proposes a new sampling method that allows for effectively sampling respondents in *relation* to their built environment. The method expands the current capability of selecting respondents of interest (e.g., particular age or race groups) to also selecting specific environments of interest based on such conditions as age of housing stock, housing type, building coverage, land uses, property value, street patterns, traffic conditions, sidewalk connectivity, and trail proximity.

Methods

We first review theoretical and analytical issues raised by traditional sampling methods frequently used in environment-behavior research. We then introduce a spatial sampling strategy using newly available parcel-level GIS data that link geospatial parcel polygons with tabular attribute data on the parcels' land uses, land values, year built, and so forth. This method integrates conceptual and spatial definitions of the study population, delineating a spatial sample frame based on the specification of environmental factors associated with the behavior of interest. An application of this new strategy in a recent study serves to demonstrate its potential as a preferred alternative to the traditional methods (14).

Traditional Sampling Methods

Many challenges in studies involving built environmental variables originate in the sampling process. Many environment-behavior research rests on a simple probability sampling drawing from an administrative boundary, sometimes stratified by a key sociodemographic variable or another administrative boundary 13, 15, 16 and 17. National health surveillance or transportation statistics have relied on this sampling technique (e.g., BRFSS[1], NPTS[2], NHTS[2]). This method is based on the population size and disregards variations in and distributions of physical environmental conditions, often resulting in few observations in rarely occurring environmental conditions and limited variability in environmental variables.

A number of recent studies employed a probability sample of respondents from a number of “nonrandomly” selected “neighborhoods,” defined by census or other administrative boundaries. These sampling approaches select neighborhoods with prespecified factors of interest to ensure a sufficient level of variability and number of observations 15, 18, 19, 20 and 21. Variables are captured at two different levels: neighborhood and individual. This increasingly popular approach has advantages and limitations, which are discussed below.

Reduced data collection costs: Neighborhood-based sampling makes an economic sense when extensive new field data collection is necessary. Spatially contained neighborhoods can reduce time and labor costs. It is especially attractive when acquisition of a complete list of sampling units is costly or unavailable.

Compensation for lack of theory on the measurement units of environment: Due to the lack of theory grounding appropriate geographical boundaries, census or administrative boundaries, loosely called "neighborhoods," have served "conveniently" as measurement units of environmental data. However, these boundaries are arbitrary and often do not correspond to actual or perceived boundaries of physical or social neighborhoods 22, 23 and 24.

Large and varying size of neighborhoods: These neighborhoods are often too large to capture detailed variations in the built environmental characteristics that may influence individual behaviors 25, 26 and 27. In addition, the size and shape of these neighborhoods vary significantly, increasing vulnerability to the Modifiable "Areal" Unit Problem (MAUP). MAUP refers to the variations in analytical results when areal units are different in size and/or spatial arrangement 28 and 29.

Limited effectiveness of stratification: Neighborhood-based sampling employs a between-neighborhood stratification based on key neighborhood-level independent variables. Stratified sampling works well if the strata are fairly homogeneous. The arbitrary nature of neighborhood definition often introduces large within-neighborhood variations of environmental conditions. Furthermore, the lack of clear thresholds for environmental conditions (of the kind that exist for such sociodemographic factors as gender and ethnicity) impedes the effectiveness of stratification (30). While, for example, the relationship between residential density and walking is well recognized, a minimum threshold of density needed to attract walking is unknown.

Limited inference due to nonprobability sampling: Neighborhood-based sampling is similar to multistage sampling, which combines cluster and stratified sampling techniques, yet it lacks randomness in selecting the primary sampling units (the neighborhoods). This nonrandomness limits the inference to only those neighborhoods that are purposively selected and puts in question the external validity of the findings.

Aggregation and disaggregation problems: Units of data collection for behavior and environmental data are inconsistent at the individual and the neighborhood levels, respectively. As a result, the unit of analysis may be either the individual respondent or the neighborhood, with both presenting potential theoretical and analytical complications (31). If the individual respondent is used as a unit of analysis, disaggregation problems occur, involving the risk of committing Type I error due to the inflated sample size (32) and spatial dependency. These problems affect both response and explanatory variables, reducing precision in estimates of means and totals, as well as regression coefficients. If the neighborhood is used as a unit of analysis, aggregation problems ensue, including a shift in the meaning of the study from the individual to the neighborhood and reduced degrees of freedom and statistical power.

Some of the limitations discussed so far may be addressed through statistical methods. Hierarchical linear models are popular for analyzing nested data. When performed correctly, these models account for the clustering of respondents within neighborhoods without falsely increasing the error degrees of freedom and confidence intervals at the neighborhood level. In mixed linear models, as a demonstration, any covariates at the neighborhood level would be tested by using the between neighborhood variance component as the error term 33 and 34; this error term is likely to be larger than the within neighborhood error term. It will also suffer from being estimated with fewer observations, which are the number of neighborhoods, than the second error term. These multilevel models also depend on meeting many complicated assumptions, without which little will be known about estimators and their properties (35). These assumptions in turn complicate the interpretation of findings and their translation into intervention strategies (23). Discussions on statistical treatments of nested data are beyond the scope of this article and can be found elsewhere 33, 36, 37 and 38. The focus of this article is to introduce a sampling strategy that reduces the occurrence of these complications, not the treatments of the problems after they occur.

Proposed Sampling Method: Spatial Sampling Based on Built Environmental Factors

The proposed method consists of a simple or a stratified random sampling of respondents, drawn from a population defined by conceptually and spatially specified environmental conditions. It allows considering and testing various environmental conditions while establishing the sample frame. Individual respondents can be used consistently as the unit of sampling, measurement, and analysis, with or without the consideration of neighborhood-level effects.

A prerequisite to establishing the sample frame is the now readily available parcel-level GIS data 39 and 40. Parcels or lots of individual residences serve as sampling units, allowing both sociodemographic data and environmental data (possibly captured at multiple spatial scales using different radii from each respondent's residential parcel) to be linked to each individual respondent's residential parcel. The parcel data have been collected worldwide for legally occupied, registered, or surveyed land parcels and, specifically, for most metropolitan areas with over 100,000 population (41). First generated for land records and tax assessment purposes, the data are typically further developed by local public agencies to include dozens of parcel attributes such as size, ownership, property value, tax status, land use, characteristics of buildings and improvements, zoning, and development capacity. They constitute rich databases of sociophysical attributes of the built environment that, although commonly used in land surveying and monitoring, have yet to be fully utilized to complement the widespread use of census data in social science research.

Spatial sampling consists of the following four steps:

1. *Define Conceptual Population.* Examples can include residents living in an environment with certain density ranges and housing types, level of urbanization, and proximity to certain land uses or amenities.

2. *Define Spatial Extent of Population and Establish Sample Frame.* The spatial extent of the conceptual study population is delineated and mapped using parcel data in GIS, with one or more continuous geographic areas making up the spatial sample frame.

3. *Examine Spatial Sample Frame.* The characteristics of the sample frame are examined for variability, distribution, and representativeness of both environmental and sociodemographic variables.

4. *Determine Sample Design and Size, and Draw Samples.* Previous steps will suggest simple or stratified sampling. Final sample size (target number of completed responses) is determined, and samples are drawn.

Application

The Walkable and Bikable Communities (WBC) project, funded by the Centers for Disease Control and Prevention (2001–2004), is used to illustrate an application of the four-step spatial sampling strategy. The project involves studying people's walking and biking behaviors in relation to their residential environment (14). It examines this relationship in environments with a minimum level of support for walking and biking, in an effort to maximize variability in environmental characteristics and to ensure sufficient numbers of walkers and bikers.

1. Define Conceptual Population. The population consists of able-bodied adults living in the urbanized areas of King County, Washington. This study focuses on areas with a minimum level of support for walking and biking, defined by medium to high residential density (10+ dwellings per acre), and close proximity (240 meters/787 feet or less) to neighborhood retail (42).

2. Define Spatial Extent of Population and Establish Sample Frame. GIS functions first capture two types of parcels defined by the criteria: residential parcels above the minimum density and parcels with specified neighborhood retail uses. Second, spatial buffering functions agglomerate the selected parcels if they are within 240 meters of each other. The outer boundaries of agglomerated parcels delineate the spatial sample frame (42). The WBC project produced a spatially discontinuous sample frame (Fig. 1).


(174K)

Figure 1. Spatial sample frame[3].

3. Examine Spatial Sample Frame. Typically the sampling objective is to select a sample that represents (resembles) the population in terms of key environmental variables being considered; randomization usually suffices to do this. However, it is also important to ensure adequate representation of rare subpopulations of interest. Distributions of many built environmental variables show highly positive skewness. Various descriptive statistics are performed to examine the sample frame, and to determine if further modification of the sample frame or stratified sample is needed. Tests also included comparisons of environmental factors between the entire sample frame and a hypothesized “pilot” random sample of respondents (tested with a few different sizes of samples; 750 was used as an example here).

Two of the key variables illustrate this process: street-block size and proximity to trails, where smaller street-blocks and shorter distance to trails are hypothesized to be associated with more walking and biking. Street-block sizes show a positively skewed distribution and range from less than 1 acre to over 500 acres. Further, empirically defined threshold guides dichotomized test, 6-acre being a maximum size for areas conducive to pedestrian travel 43, 44 and 45. About 54% of the total residential units in the sample frame are in small, and the remaining 46% are in large blocks (Table 1). Sample frame and pilot sample have a comparable distribution of residential units in small and large blocks, making a stratification of the sample based on block size unnecessary.

Table 1.

Distribution of street-block size in spatial sample frame and pilot sample

	Spatial Sample Frame		**Pilot Sample**	
	Number of Residential Units	**Percent**	**Number of Residential Units**	**Percent**
Small Blocks (up to 6 acres)	179,452	54%	439	59%
Large Blocks (6+ acres)	150,990	46%	311	41%
Total	330,442	100%	750	100%

Second, the distribution of dwelling units in relation to their proximity to trails is examined. The histogram shows a pattern of Poisson distribution with little dispersion and skewness, requiring no need for stratification (Fig. 2).

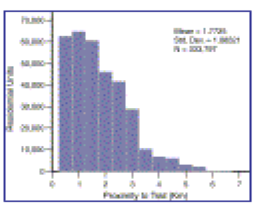

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Figure 2. Distribution of proximity to trails in spatial sample frame.

Additional tests are conducted to further understand the characteristics of the spatial sample frame, which is crucial to interpret the findings within appropriate regional contexts and to avoid over generalization. Housing types (single-family versus multifamily) and locations *(within* versus *outside* the City of Seattle corresponding to older *urban* versus newer *suburban* areas), and land use compositions are used as examples (Table 2). The spatial sample frame contains a higher proportion of multifamily units than the larger region, King County, as expected from the definition of the conceptual population for this study. Again, however, the proportion of housing types and locations are similar between the sample frame and the pilot sample. This sample frame aims at sufficiently including areas with proximate and diverse destinations for walking and biking, especially in the suburban areas. Descriptive statistics confirm that these potential destinations, such as neighborhood retail, office, or education uses, are better represented in the spatial sample frame compared to the entire suburban area (Fig. 3).

Table 2.

Distributions of housing type and location in King County, spatial sample frame, and pilot sample

			Housing Type				**Location**			
	Total Residential		**Single Family**		**Multi-Family**		**Urban**		**Suburban**	
	Units	**%**	**Units**	**%**	**Units**	**%**	**Units**	**%**	**Units**	**%**
King County	669,385	100	410,210	61.3	259,175	38.7	247,294	36.9	422,091	63.1
Spatial Sample Frame	335,277	100	97,961	29.2	237,316	70.8	199,737	59.6	135,540	40.4
Pilot Sample	750	100	215	28.7	535	71.2	452	60.3	248	39.7

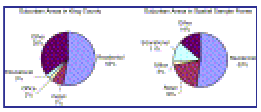
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Figure 3. Distribution of land uses in suburban areas in King County and in spatial sample frame.

4. Determine Sample Design and Size, and Draw Samples. WBC used a design-based approach for the sampling design to obtain a fair and objective sample (46), after ensuring that subpopulations of interest are well represented in the previous step. For estimation of regression coefficients (correlations) between built environment and walking/biking, some (purposive) balanced designs would most likely result in more precise estimators 47 and 48. However, methodological difficulties arise when there are many auxiliary variables such as in this project. Furthermore, a simple design was desired so that design-based corrections to regression coefficient estimators are not necessary (that is, corrections other than simply ignoring the finite population correction).

Sample size calculations are often difficult because, even in the case of a simple linear regression, they require advance information on the attributes of population, which may not be available. Sample size estimations become more complicated with more complicated analyses, such as multiple regression (49), logistic regression (50), Poisson regression (51), and hierarchical models 32 and 52. Sample size calculations for the WBC project reflect a series of constraints, including lack of necessary information on the key behavioral attributes (walking and biking) and the large number of independent variables considered (41). The simplified method used determines the sample size necessary to estimate the mean of a Poisson random variable for the number of walking or biking trips per week and a binomial random variable for the probability of being a walker or a biker with a given precision, which is then adjusted for the number of auxiliary measurements to be used. The final sample size of 750 is informed by this calculation, but it also reflects the project budget and pilot sample testing results in the previous step. Because the unit of analysis is the individual, not the neighborhood, there are 750 degrees of freedom for regression analyses. The WBC project uses telephone surveys, and, considering the nonresponse and frame errors and contactability, about 3500 randomly selected phone numbers are drawn and called.

Results

Spatial sampling is preferred over neighborhood-based sampling for the WBC project. First, spatial sampling allows researchers to translate conceptually defined sample frame into empirically tested sampling decisions to maximize the power and to economize the cost of the study. Had neighborhood-based sampling been used, the units of analysis would be both the neighborhood and individual, thus requiring a much greater number of respondents. At least 15, but probably more, neighborhoods would likely be needed to fit regression models. And approximately 100 to 150 respondents from each neighborhood would have been required given comparable specifications used for the spatial sampling. Although direct comparisons of samples sizes are not possible, spatial sampling tends to require a much smaller number of respondents for a given power than does neighborhood-based sampling.

Second, neighborhoods could be selected based on population density and the presence of nearby neighborhood retail, but the delineation of neighborhood boundaries would be difficult, as would the definition of neighborhood centers. Researchers agree that “one size fits all” is inappropriate, and that a multiplicity of sizes, shapes, and center locations is needed to capture temporal and structural delimitations of areas that people perceive and use as neighborhoods 21, 22, 23 and 29. Spatial sampling does not impose a prespecified neighborhood, and allows respondents to define their own neighborhoods, based on their behavior, experience, perception, or individual choice (53). Data collected from the individuals can be used later to establish valid neighborhood boundaries for considering neighborhood-level effects.

Third, the clustering of respondents into some 15 predefined neighborhoods would have severely limited the generalizability of the study and introduced additional complications during the statistical analyses. Spatial sampling was shown to be cost-effective because it required a smaller sample size, and its results were generalizable to a larger population size, compared to the neighborhood-based method. Also, its use of existing parcel data as sampling units eliminated the need to acquire extensive list of sampling units, which can be costly.

Spatial sampling is not without challenges. For studies involving face-to-face interviews or fieldwork, the spatial sample frame tends to be more labor intensive, as it involves more dispersed locations of respondents than in neighborhood-based studies. Yet gains in the generalizability of results may outweigh possible increases in data collection costs. Another limitation is the reliance on databases that are new to public health research. Although available in most urban and suburban jurisdictions, parcel-based land use and assessor's data may take time to acquire and get familiar with. Data accuracy is typically limited to taxable land uses, but different local agencies can provide additional data layers on publicly owned properties, such as parks, which are compatible with assessor's data. In the WBC project, data development included random field verifications, cross-referencing with other existing data, verification of land use codes, and treatment of missing data. The process took about 2 months for the entire parcel dataset, which was over 500,000 records.

Conclusion

Spatial sampling is innovative for its capability to consider built environmental conditions while establishing the sample frame and drawing the samples. Based on parcel-level sociophysical data, the method allows researchers to control the specific environmental conditions they want to study, in terms of their specificity, variability, and distribution.

The proposed spatial sampling method permits the use of the individual as the unit of sampling, data collection, and analysis (consistency); reduces the number of observations necessary (economy); and discourages the potentially erroneous a priori definition of neighborhoods (accuracy). It allows testing the strength of individual environmental variable and establishing empirically tested thresholds by which neighborhood types can be selected (e.g., density, mixed use, or connectivity thresholds). Such validated thresholds will allow traditional neighborhood-based studies to be carried out more effectively.

By expanding the range of fine-resolution environmental variables that can be quantitatively studied, this spatial sampling method can help find new or stronger environment-behavior associations. It promises to contribute to the growing number of studies based on the social-ecologic model.

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[3] It includes a large contiguous area containing many of Seattle's neighborhoods, and a series of smaller patches scattered around in the suburban areas of the King County. Together, the spatial sample frame covers more than 88 square miles, or 19% out of the 464 square miles that constitute the urbanized areas of King County, WA.

[1] Behavioral Risk Factor Surveillance System conducted by the Centers for Disease Control and Prevention, US Department of Health and Human Services.

[2] Nationwide Personal Transportation Survey and Nationwide Household Transportation Survey conducted by the US Department of Transportation and National Highway Administration.

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