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Home Versus Nonhome Neighborhood:

Quantifying Differences in Exposure to the Built Environment

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Abstract

Introduction—Built environment and health research have focused on characteristics of home neighborhoods, whereas overall environmental exposures occur over larger spatial ranges.

Purpose—Differences in built environment characteristics were analyzed for home and nonhome locations using GPS data.

Methods—GPS data collected in 2007–2008 were analyzed for 41 subjects in the Seattle area in 2010. Environmental characteristics for 3.8 million locations were measured using novel GIS data sets called SmartMaps, representing spatially continuous values of local built environment variables in the domains of neighborhood composition, utilitarian destinations, transportation infrastructure, and traffic conditions. Using bootstrap sampling, CIs were estimated for differences in built environment values for home (<833 m of home address) and nonhome (>1666 m) GPS locations.

Results—Home and nonhome built environment values were significantly different for over 90% of variables across subjects ($p<0.001$). Only 51% of subjects had higher counts of supermarkets near than away from home. Different measures of neighborhood parks yielded varying results.

Conclusions—SmartMaps helped measure local built environment characteristics for a large set of GPS locations. Most subjects had significantly different home and nonhome built environment exposures. Considering the full range of individuals' environmental exposures may improve understanding of effects of the built environment on behavior and health outcomes.

Introduction

Recent studies have demonstrated relationships between aspects of the built environment and physical activity, walking, and other health-related behaviors. This past research suggests that built environment modifications may promote health by providing places supporting active lifestyles.[1–3] In view of the limited success of individually based interventions, built environment modifications may be a promising avenue for improving health outcomes and countering the obesity epidemic.[4]

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This paper addresses two questions raised by previous research showing relationships between environment and physical activity. First, most studies focused on respondents' home neighborhoods, measuring environmental attributes within a predefined distance of homes.[5,6] Whereas people spend considerable time away from home, and may be active at work, school, or recreation locations, only a few studies investigated the role of the work neighborhood on activity.[7–9] In fact, people visit, move through, and hence are exposed to multiple neighborhoods during a typical day. Thus, research considering only home neighborhoods may erroneously attribute built environment effects on behavior to the home environment, while ignoring possible effects of other environments. The conceptualization of exposure to nonhome environments has been addressed by several researchers.[10–14] In one study, including characteristics of nonresidential census tracts was found to affect models of self-reported health.[15]

A new trend in research uses GPS to measure location-specific activity of individuals as they move through space.[9,16–20] One study used GPS and accelerometry data to aggregate built environment values within predefined distances to both home and work locations, measuring time spent in moderate-to-vigorous physical activity (MVPA) within each of those buffers.[9] It showed that while total MVPA was not associated with either home or work neighborhoods, physical activity occurring within each neighborhood was related to different neighborhood-level environmental attributes.

Another study using GPS and accelerometry found differential patterns in MVPA between home and nonhome neighborhoods.[21] Also, adolescent girls tracked with GPS-enabled cell phones were found to spend substantial time further than 1 km from home.[22] Analyses based on objective measures of activity and location thus suggest that relating activity solely to home neighborhoods may lead to spurious associations between environment and behavior. There is a need to capture environmental exposure across space and time, and to devise a measurement framework that allows quantifying peoples' activity and characteristics of the built environment where activity occurs.

Second, using GPS and accelerometry to capture individual movements generates very large data sets. Recording a GPS track during a normal 10-hour day would yield 36,000 locations per individual (for a 1-second sampling interval). These locations effectively represent a sample of the many neighborhoods to which people are exposed during daily activities. The inclusion of multiple neighborhoods in modeling environmental influences on activity is supported by past research documenting the multiplicity of neighborhoods with which individuals routinely interact.[23–25] At the same time, it introduces data capture and measurement challenges that are nontrivial even in today's advanced computational environment.

The current study offers a new framework for measuring environment continuously through space, allowing measurement of local environmental attributes for massive numbers of locations such as those obtained using GPS. The study also analyzes differences in the built environment characteristics of home and nonhome locations.

Methods

Population

The original convenience sample consisted of a group of 51 students, staff, and faculty of the University of Washington (UW). Subjects gave signed consent and completed a brief demographic survey, including home addresses that were geocoded to the nearest street intersection. Subjects were instructed to wear the combined sensor device (described below) for 7 consecutive days. The study protocol was approved by the University of Washington IRB and data were collected between November, 2007 and May, 2008.

Geospatial Location Data

Movement and location were measured using a novel sensing device, the Multi-Sensor Board (MSB), which contained independent sensors for 3D accelerometry, temperature, humidity, barometric pressure, UV and high-frequency light, compass bearing, and audio.[26] The sensors were housed in a pager-sized plastic box worn at the waist. Subjects recharged the MSB each night.

Geospatial location was measured with an integrated SiRF III GPS receiver recording at 1 Hz, with accuracy <2.5 m (CSR, Cambridge, UK). GPS data were cleaned using automated and manual data processing. Locations with less than four satellites or horizontal dilution of precision ≤ 8 were automatically deleted. ArcGIS 9.3.1 (ESRI, Redlands, CA) was used interactively to remove obvious spatial outliers. For efficient handling of the large point data sets, most data storage and processing used PostGIS 1.51.[27]

Built Environment Data

The GIS data representing built environment variables covered King County, WA (KC) (population 1.9 million in 5500 km^2). Tax parcel polygon data, from KC GIS (KCGIS) and the KC assessor, included attributes describing count of residential units and predominant land use, which was used to estimate per-parcel employment counts based on land use.[26] KCGIS also provided street and regional trail data. Traffic data came from the Puget Sound Regional Council. Food establishment data were developed by the University of Washington Urban Form Lab (UFL), based on geocoded food permits obtained from Public Health—Seattle KC. Bus ridership data were obtained from KC Metro. Park data were compiled by the UFL from individual jurisdiction GIS layers. Physical activity and fitness facility data came from InfoUSA, and were geocoded by the UFL.

SmartMap Measurement

A novel approach to the measurement of the built environment was required to accommodate the original 4.3 million GPS locations. Previous approaches used buffers around subjects' home locations to extract and summarize GIS data within the local neighborhood, storing summary values as individual-level variables.[5] This point-centric approach requires a substantial amount of data processing for each location, and it is too computationally intensive to be practical for large GPS data sets collected in free-roaming conditions.

In this study, rather than performing point-centric built environment measures at all GPS locations, a set of raster layers[28]—spatially continuous surfaces of grid cells—was created for efficient measurements at any number of locations within the study area. These rasters are referred to as SmartMaps. The point value at each SmartMap cell represents a summary of the local neighborhood value around the cell. SmartMaps provide the same data as in the traditional buffer method. However, instead of recording neighborhood summaries at specific predefined point locations, SmartMaps do so for every cell, continuously across space, enabling measures at any location in the study area.

SmartMaps were created using focal raster processing. The study area (KC) was represented as a 30x30 m grid, which was previously shown to represent urban and suburban parcels with sufficient spatial fidelity.[29] Each "focal" grid cell was processed independently using the ArcGIS Spatial Analyst Extension. Prescribed analytic steps were performed for the area around the focal cell, placing the resulting value on the focal cell, then moving to the next cell, repeating the process until values were calculated for all cells in the study area.

For the set of SmartMaps used in this study, an 833-m radius circle was selected to represent the focal "neighborhood"—a distance that could be walked in 10 minutes. For example, to calculate a SmartMap of residential unit counts within 833 m of a grid cell, parcels were converted to a raster, in which cell values represented the fraction of residential unit counts within the cell (e.g., a 9000 m^2 parcel containing 20 residential unit counts yielded 10 cells with a value of 2 units/cell). The process then summed the values of all cells within each focal buffer to represent the number of residential unit counts for the focal cell's neighborhood. SmartMap cell values were extracted for GPS points using the Surface Spot method in ArcGIS.

Fifteen SmartMaps served to characterize built environment elements in domains which past research had associated with physical activity and obesity. Neighborhood composition was represented by counts of employees and residential units.[30,31] Utilitarian destinations were captured as counts of supermarkets, fast food and traditional restaurants, coffee shops, and fitness facilities,[32,33] and by count, area, and percentage of neighborhood covered by parks.[34,35] Transportation infrastructure was measured as intersection, street, and trail density.[30,36–38] Traffic conditions included estimated traffic volume[39] and bus ridership.[40]

Analyses

Analyses used the entire set of subjects' GPS points on an individual basis. To examine differences in built environment values between home and nonhome locations, GPS points were dichotomized as being within 833 m (<10 minute walk), and beyond 1666 m (>20 minute walk) from the home address. GPS points situated between 833 and 1666 m were discarded to clearly separate GPS locations associated with home and nonhome environments.

The very large number of observations meant that typical statistical methods for comparing built environment characteristics of home and nonhome locations (e.g., t- or Wilcoxon tests) produced greatly inflated significance values. Instead, bootstrap sampling served to estimate the empirical distribution of observed data, as parametric assumptions were not met.[41] After dichotomizing each subject's data into home and nonhome location bins, six records per hour were randomly sampled from each bin. These values were used to calculate the median for each built environment SmartMap variable and the difference between the home and nonhome median values. This process was repeated 10,000 times, resulting in a difference of medians for all bootstrap samples for each subject by built environment variable.

A 95% CI was constructed from the set of differences of medians; if the 95% CI did not contain 0, then the home and nonhome built environment characteristics were determined to be significantly different.[42] A set of CIs was constructed for all subjects, and the total number of subjects with significantly higher, lower, or no difference, in median values between home and nonhome environment built environment variables were tallied for X^2 testing. Programming of the bootstrap and other statistical analyses were conducted using R 2.9.0.[43]

Results

Population

The final study sample included 41 adults (10 subjects had no data either near or away from home). The mean age was 32 years, and the sample was predominantly male (64%). Most subjects were white (72%), with 23% Asians and 5% Hispanics. The sample was highly educated, with more than 90% possessing college degrees. Income was bimodally distributed, with more than 61% of subjects earning less than $25,000 annually, and 26% earning greater than $51,000. The sample included 80% of subjects in the normal BMI category, 15% overweight, and 5% obese (data not shown). The mean network distance from subjects' homes to campus was 8.7 km (SD 10.0).

GPS Locations

The 41 subjects yielded a total of 3.8 million GPS records (the 10 dropped subjects accounted for 0.5 million dropped points). Automated and manual data cleaning removed 16% of the raw GPS locations. Table 1 shows that the count of GPS locations for home and nonhome was about equally divided, with 5.8% of locations between 833 and 1666 m from home (discarded). Most GPS locations were concentrated in the western and developed part of KC, where the majority of people live (Appendix A, available online at www.ajpmonline.org). The mean Euclidean distance between each GPS location and the UW campus was 8.5 km (SD 21.7), with 52% of locations more than 3 km from campus. Approximately 3.8 hours of data were collected per subject per day (range: 0.4–6.8 hours; median: 3.2 hours).

SmartMaps

Each of the 15 SmartMaps of KC contained 6.8 million 900 m^2 cells, with each raster providing the neighborhood value for separate built environment variables. Appendix A (available online at www.ajpm-online.org) shows a SmartMap of residential unit count for the greater Seattle area. SmartMap data had a wide range of built environment values (Table 2). Differences in mean built environment values between home and nonhome locations were split almost equally between higher and lower values.

In the neighborhood composition domain, mean residential unit counts ranged from 2700 for nonhome locations (12.4 units/ha) to 4,600 (21.3 units/ha) for locations near home. Employment counts had a greater range; the nonhome location mean was 12,600 (56.8 employees/ha), whereas home locations' mean was 7100 employees (32 employees/ha). In the traffic conditions domain, there were similarly higher values for traffic volumes and bus ridership of nonhome than of home locations. However, in the transportation infrastructure domain, street and intersection density were lower in locations away from home than near home. Trail density was twice as high in nonhome locations than in home locations. In the utilitarian destinations domain, home locations had lower values than nonhome locations for traditional and fast food restaurants, and for total park area. Home locations had higher values for supermarkets, coffee shops, fitness facilities, park count, and percentage of neighborhood in park.

Built Environment Characteristics at GPS Locations

There was considerable intra-subject variation in home and nonhome built environment variable values. Appendix B (available online at www.ajpmonline.org) shows that for Subject 19, the 95% CI of the difference of medians for residential unit counts between home and nonhome locations ranged from −175 to 485, indicating no difference for home and nonhome neighborhoods; for Subject 67, the 95% CI did not include 0, indicating that home and nonhome neighborhoods had significantly different residential unit counts.

Intersubject variation in residential unit count CIs is shown in Appendix C (available online at www.ajpmonline.org) (left). The *y*-axis represents home medians minus nonhome medians for each subject; and the vertical bars represent the 95% CI. Subjects with *y*-axis values less than 0 had lower residential density near home, whereas those with values above 0 had higher residential density near home. About two thirds of subjects had higher residential density near home, and only one subject had no difference in residential density near home versus away from home. The full set of CI graphs for all subjects' built environment variables is available in Appendix D (available online at www.ajpmonline.org).

Bootstrap sampling of the full set of subjects and built environment variables (n=615; 41 subjects × 15 built environment variables) showed significant differences between home and nonhome locations (X^2 p<0.001). About 48% of the subject built environment values (n=292) were significantly higher near home than away from home; 44% (n=272) were significantly lower; and 8% (n=51) showed no difference (Appendix C, right, available online at www.ajpmonline.org). Median built environment values were significantly higher in home than nonhome neighborhoods for counts of residential units, supermarkets, fitness facilities, and parks; for percentage of neighborhood in park; and street and intersection density. Values were significantly higher in nonhome locations for counts of employees, fast food and traditional restaurants, and coffee shops; and for park size, trail density, traffic density and bus ridership. Of the 8% of the subject built environment values with no significant difference between home and nonhome locations, most were for percentage area in parks, trail density, and counts of supermarkets.

Discussion

To the authors' knowledge, this is the first study to combine high-frequency GPS data with spatially continuous measures of built environment. Based on high-resolution and objective data, the approach showed that more than 90% of the built environment values at locations near individuals' homes were significantly different from those away from individuals' homes.

Built environment attributes selected for inclusion were those that past studies associated with physical activity, overweight/obesity, and diet-related behaviors. Differences in built environment variable values measured with SmartMaps for home and nonhome locations might therefore explain inconsistent results among past studies attributing exposure at subjects' homes rather than at all activity locations. Differences found between home and nonhome environments were expected for some variables. Near home, residential density was higher and employment density lower; and away from home, traffic counts and bus ridership were higher, reflecting the typically contrasting characteristics of residential and work places. However, results for other variables suggested further study.

Supermarkets have been the focus of many obesity-related studies,[44–46] yet only 51% of subjects had more supermarkets near than away from home. Also, a large proportion of subjects had no difference in the number of supermarkets between home and nonhome locations. This finding suggested that exposure to supermarkets varied less than exposure to other utilitarian destinations, such as fast food and traditional restaurants, and coffee shops, whose counts were higher in nonhome locations.

Further, differing measures of the presence of parks yielded differing results; size and count of parks were different between home and nonhome environments for most subjects, but the percentage of area in park showed no differences for about one quarter of the subjects. Thus, capturing the potential influence of parks on behavior might be highly dependent on the measures used.[47,48] The findings pointed to the importance of considering nonhome environments in future estimations of exposure to the built environment. They mirrored other GPS and accelerometry-based studies that investigated environmental influences on physical activity, often observed outside of home or work neighborhoods.[9,21]

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Strengths and Limitations

Methodologically, this study presented a theoretically and operationally simple framework for associating local neighborhood built environment characteristics with locations where activities occurred. It took a step forward in estimating the effects of exposure to the multifarious environments to which individuals are exposed on a daily basis.

Using SmartMaps to obtain environmental measures for point locations was considerably more efficient than performing a series of point-centric buffer analyses for locations of interest. It took less than 1 hour per SmartMap to extract built environment data for the 3.8 million collected GPS locations. Although the creation of SmartMaps required a substantial amount of effort, once created, the rasters could be readily used for any study analyzing point measures of environment within the study area.

SmartMaps would be useful either in traditional health studies assessing home or work environment for large numbers of participants, or in the growing number of studies in which individual movements are tracked using geolocational technologies. Ideally, urbanized regions could develop sets of SmartMaps for use by multiple agencies or research entities monitoring or analyzing the effects of built environment on behavior, as has been done in other fields such as meteorology and noise mitigation.[49] Further, SmartMaps may be archived from data sources measured at different points in time, for use in longitudinal studies.

Limitations included the small convenience sample, with a relatively large proportion of young adults. Also, subjects shared the UW campus district as a work environment, which could have introduced bias in the nonhome built environment values, despite the area's large size (about 400 ha) and varied residential, commercial, and open space uses. As with all cross-sectional studies, self-selection of residential locations, as well as locations visited throughout the day, may have played a role in determining the built environment characteristics of subjects' activity space, although even for this small sample, residential locations were widely distributed across the study area.

The GPS data were temporally incomplete. The 3.8 million data points represented about one third of those that would have been collected had the battery of the experimental MSB devices maintained their charge for a full day. Thus, the data on visited locations were likely biased toward locations visited earlier in the day.

The SmartMaps were created using circular, rather than network buffers. This basic limitation in the ArcGIS focal processes will be addressed in further methods development. Finally, a 10- minute walking-distance equivalent (833 m) was used to capture features of the built environment that were reasonably accessible by walking. Future studies should select and test optimal bandwidths for measuring local neighborhood characteristics with respect to particular facilities, behaviors, or health outcomes.

Conclusion

This study introduced a conceptual and methodologic framework to quantify personal environmental exposures across space and time. The use of SmartMaps facilitated measurement of local neighborhood built environment characteristics for a very large set of GPS track points. Findings showed that most home built environment exposures were different from nonhome built environment exposures. These methods could be applied to future research investigating associations of built environment with health-related behaviors or health outcomes. Whereas existing studies have focused nearly exclusively on the home neighborhood, the proposed methods could be used to estimate complete built environment exposures across individuals' entire activity space. Taking into account the full range of environmental exposures may lead to more-consistent results and hence a better understanding of the relationship between built environment, behavior, and health outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

GPS location counts by distance to home and the University of Washington campus main entrance

	Distances (m)			
	<833	833–1666	>1666	All
TO HOME				
All observations				
%	48.6	5.8	45.6	100
Count (millions)	1.9	0.2	1.7	3.8
By subject				
% (SD)	48.1 (27.3)	8.4 (11.5)	45.7 (24.4)	100
Count: M (SD)	45,182 (33,728)	5,446 (6,622)	44,592 (33,506)	93,044 (43,598)
TO UNIVERSITY OF WASHINGTON				
All observations				
%	24.1	14.1	61.8	100
Count (millions)	0.9	0.5	2.4	3.8
By subject				
% (SD)	26.0 (24.2)	15.4 (22.8)	61.1 (30.0)	100
Count: M (SD)	23,023 (23,396)	13,466 (25,403)	55,881 (42,136)	93,044 (43,598)
M (SD) distance				8,487 (21,712)

Table 2

SmartMap built environment values by domain, M (SD)

	All[a]	**Home**	**Nonhome**
Neighborhood composition			
Residential units (count × 1000)	3.7(3.5)	**4.6 (4)**[2]	2.7 (2.3)
Employment (jobs × 1000)	10.4(15.3)	7.1 (12.4)	**12.6 (14.9)**
Utilitarian destinations			
Supermarkets (count)	0.8(1.2)	**1.0 (1.3)**	0.7 (0.9)
Traditional restaurant (count)	8.3 (11.3)	7.7(10)	**8.4 (11.4)**
Fast food restaurants (count)	3.8 (4.3)	3.3 (4.2)	**4.1 (4.2)**
Coffee shops (count)	8.9(11.5)	**8.9 (11.7)**	8.4(10.5)
Fitness facilities (count)	1.6(1.7)	**1.9 (1.9)**	1.3(1.4)
Park area (ha)	41 (806.9)	30.6 (42.8)	**54.1 (1175.0)**
Parks (count)	3.7(2.3)	**4.0 (2.3)**	3.4(2.2)
Park area (%)	5.4 (7.9)	**7.1 (9.3)**	3.9(6.1)
Transportation infrastructure			
Street density (km/km^2)	13.6(5.0)	**14.2 (4.9)**	12.9(5.0)
Trail density (km/km^2)	0.5 (0.5)	0.3 (0.4)	**0.6 (0.5)**
Intersection density (count/km^2)	177.4 (78.0)	**181.1 (75.4)**	170 (79.8)
Traffic conditions			
Traffic volume (1000 vehicles)	115.3 (101.1)	97.2(101.9)	**128.7 (95.5)**
Bus ridership (count × 1000)	14.9(19.2)	9.3 (13.4)	**19.8 (21.4)**

[a]all = all GPS locations; home = GPS locations within 833 m of home locations; nonhome = GPS locations beyond 1666 m of home locations

Note: Bold indicates higher value for home than nonhome.