HHS Public Access
Author manuscript
Res Q Exerc Sport. Author manuscript; available in PMC 2019 September 01.

Published in final edited form as:
Res Q Exerc Sport. 2019 September ; 90(3): 395–402. doi:10.1080/02701367.2019.1609649.

Accelerometer and GPS data to analyze built environments and physical activity

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Abstract

Purpose: Most built environment studies have quantified characteristics of the areas around participants' homes. However, the environmental exposures for physical activity (PA) are spatially dynamic rather than static. Thus, merged accelerometer and global positioning system(GPS) data were utilized to estimate associations between the built environment and PA among adults.

Methods: Participants (N = 142) were recruited on trails in Massachusetts and wore an accelerometer and GPS unit for 1–4days. Two binary outcomes were created: moderate-to-vigorous PA (MVPA vs. light PA-to-sedentary); and light-to-vigorous PA (LVPA vs. sedentary). Five built environment variables were created within 50-meter buffers around GPS points: population density, street density, land use mix (LUM), greenness, and walkability index. Generalized linear mixed models were fit to examine associations between environmental variables and both outcomes, adjusting for demographic covariates.

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Contributors
KT conceived the study. Data acquisition was performed by PT, and data cleaning and management by KT. Analyses were performed by KT and reviewed by KG. KT drafted the initial manuscript and all authors reviewed and provided their feedback. All authors read and approved the final manuscript.

Competing interests
There are no competing interests reported by the authors of this article.

Patient consent
Participants provided written informed consent and were told that the purpose of the study was to objectively monitor physical activity and locations where physical activity occurred outside.

Ethics approval
The Institutional Review Board at Purdue University and the Human Subjects Committee at the Harvard T.H. Chan School of Public Health approved the study procedures.

Results: Overall, in the fully adjusted models, greenness was positively associated with MVPA and LVPA (odds ratios [ORs] = 1.15, 95% confidence interval [CI] = 1.03, 1.30 and 1.25, 95% CI = 1.12, 1.41, respectively). In contrast, street density and LUM were negatively associated with MVPA (ORs = 0.69, 95% CI = 0.67, 0.71 and 0.87, 95% CI= 0.78, 0.97, respectively) and LVPA (ORs = 0.79, 95% CI = 0.77, 0.81 and 0.81, 95% CI = 0.74, 0.90, respectively). Negative associations of population density and walkability with both outcomes reached statistical significance, yet the effect sizes were small.

Conclusions: Concurrent monitoring of activity with accelerometers and GPS units allowed us to investigate relationships between objectively measured built environment around GPS points and minute-by-minute PA. Negative relationships between street density and LUM and PA contrast evidence from most built environment studies in adults. However, direct comparisons should be made with caution since most previous studies have focused on spatially fixed buffers around home locations, rather than the precise locations where PA occurs.

Keywords

Recreational and utilitarian activities; neighborhood environment characteristics; multilevel data analysis

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It is well-documented that regular physical activity (PA) is beneficial for primary (i.e., risk reduction before the onset of disease) to tertiary prevention of chronic diseases (i.e., reducing impact of diseases) (2018 Physical Activity Guidelines Advisory Committee, 2018). Over the past two decades, there has been a dramatic shift in strategies for PA promotion from those predominantly focused on intrapersonal factors, such as self-efficacy for PA, to those emphasizing the influence of neighborhood environmental factors (Sallis et al., 2006). A recent review of PA interventions conducted by the U.S. Community Preventive Services Task Force provided supportive evidence for several environmental and policy approaches for promoting and supporting regular PA, including improved connectivity of sidewalks, trail infrastructure, pedestrian-oriented streets, enhancing access to public transit, and better lighting (Community Preventive Services Task Force, 2016).

The majority of PA and built environment studies have focused on fixed areas around participants' homes in relation to PA (Perchoux, Chaix, Cummins, & Kestens, 2013; Rainham, McDowell, Krewski, & Sawada, 2010). For example, it has been a common practice to obtain home addresses from study participants, geocode these addresses, and then, using various types of buffering approaches (e.g., circular buffers, line-based road network buffers), quantify different built environment characteristics within the buffers. One key limitation with this approach is the potential for a spatial mismatch between built environment exposures and the locations where PA takes place (Tamura et al., 2019). Adults are generally mobile and engage in daily activities, including PA, that are not restricted to locations close to their homes (Holliday, Howard, Emch, Rodriguez, & Evenson, 2017). Therefore, relevant built environment exposures for physical activities, such as walking and bicycling, are more spatially dynamic rather than static (Chaix, Meline, et al., 2013; Holliday, Howard, Emch, Rodriguez, & Evenson, 2017). Recent time-use surveys of U.S. adults have shown that many engage in exercise and sports activities approximately 25% of the time outdoors, 25% of the time at home, 8% at gyms, 3% at work, 36% at unspecified locations, and 3% at uncommon places (e.g., subway) (Dunton, Berrigan, Ballard-Barbash, Graubard, & Atienza, 2008).

Simultaneous use of accelerometers and global positioning system (GPS) devices permits researchers to spatially and temporally link built environment exposures to PA. Recent studies have used GPS units to identify various locations where PA occurs (Chaix, 2018; Evenson, Wen, Hillier, & Cohen, 2013; Krenn, Titze, Oja, Jones, & Ogilvie, 2011; Troped, Wilson, Matthews, Cromley, & Melly, 2010). Only a few studies using both accelerometer and GPS methods have spatially quantified PA and sedentary behavior occurring among adults (Chaix et al., 2016; Troped et al., 2010). One study utilized 1 kilometer (km) buffers around participants' homes to quantify participants' residential areas (Troped et al., 2010). They found that population and intersection density, and land use mix (LUM) were positively associated with MVPA occurring within the buffer, but not with total MVPA at any location (Troped et al., 2010). One recent study using accelerometer data linked to GPS-derived trips demonstrated that walking during a trip was 1.37 times greater in the fourth quartile of all service density (e.g., public services), compared to the first quartile (Chaix et al., 2016). Despite these findings, few studies have directly linked PA to built environment exposures via accelerometer and GPS monitoring, especially among adults. Therefore, the aim of the present study was to examine relationships between built environment variables and minute-by-minute MVPA and LVPA linked to outdoor locations via GPS coordinates. The current analysis focused on outdoor PA occurring at all locations, but excluded indoor PA facilities (e.g., gym).

Methods

Study participants

During the fall of 2004 and spring/summer of 2005, 1194 adults, aged 19-78 years, completed brief intercept surveys while they were engaging in various types of PA (e.g., walking, jogging/running, bicycling, or in-line skating) at five trails in Massachusetts, detailed methods fully described previously (Tamura et al., 2018). Respondents who reported using a trail at least four times in the past four weeks were recruited to participate in a sub-study and asked to wear an Actigraph™ accelerometer (Model 7164; Actigraph™, Pensacola, FL) and a GeoStats-GeoLogger™ (Atlanta, GA) GPS unit for four days (i.e., two weekdays and two weekend days). Among the survey participants, 294 (24.6 %) agreed to take part in this study and provided contact information. However, 116 individuals did not participate due to loss of interest in the study, scheduling conflicts, or could not be contacted. Consequently, two devices were deployed to 178 adults (Troped et al., 2010).

Data collection

Research staff met with participants to instruct them how to wear the accelerometer and GPS units and to provide daily wear logs for both devices. Participants were asked to wear the accelerometer for four consecutive days, except while sleeping, bathing, or swimming. Participants were instructed to wear the GPS unit during all time spent outdoors (i.e., irrespective of whether they engaged in any forms of PA, such as walking, bicycling, etc., or spent time in sedentary behaviors while driving, taking public transportation, or sitting outdoors). The accelerometer was programmed to collect data using 1-minute epochs. The GPS unit was programmed to collect data at 5-second intervals.

Data processing

Data processing procedures for the accelerometer and GPS data were described in more detail previously (Troped et al., 2010). In brief, a research analyst downloaded the raw GPS data using GeoStats software (Atlanta, GA). To identify outliers, the analyst manually reviewed GPS points for each participant over their entire monitoring period. GPS points were aggregated to one-minute intervals with latitude and longitude for both the starting and ending points of each minute.

Accelerometer data were downloaded using Actigraph software. Data from the accelerometer and GPS unit were merged using their date and time stamps. Each minute of GPS recordings was linked to the corresponding accelerometer count for that minute. A valid monitoring day for the accelerometer was defined as a day with ≥ 600 minutes of valid wear time (Matthews et al., 2008; Troiano et al., 2008). A valid day also required ≥ 40 minutes of GPS data; the rationale for this approach was described in a previous study (Troped et al., 2010). We included participants who had a minimum of 1 valid day of monitoring (possible range was 1 to 4 days). The breakdown of valid monitoring days by participant was: 19 (13%) participants had 1 day; 25 (18%) had 2 days, 30 (21%) had 3 days, and 68 (48%) had 4 days. One hundred forty-eight out of 178 participants had at least one valid monitoring day based on the two criteria. Six participants were excluded due to not living in Massachusetts (n=4) or not providing demographic information (n=2), resulting in a final sample of 142 individuals (Tamura et al., 2018). Accelerometer data without GPS points and GPS points without accelerometer data were excluded from the analyses. The unit of analysis was minute-by-minute PA (n=60,335).

PA outcomes

Intensity of activity was classified using activity count cut-points developed by Matthews and Crouter (Crouter, DellaValle, Haas, Frongillo, & Bassett, 2013; Matthew, 2005): 0-99 counts = sedentary; 100-759 counts = light; 760-5724 counts = moderate; and ≥ 5725 counts = vigorous. Two binary PA outcomes were created for each monitoring minute: moderate-to-vigorous PA (MVPA=1) versus sedentary-to-light activity (=0) and light-to-vigorous intensity PA (LVPA=1) versus sedentary (=0). This categorization for LVPA was consistent with the previous studies that assessed non-sedentary time versus sedentary time among adults (Cerin et al., 2016).

Built environment variables

Five objective built environment variables were created: population density, street density, land use mix (LUM) (Troped et al., 2010), walkability (Frank, Schmid, Sallis, Chapman, & Saelens, 2005), and greenness (Lindsey, Wilson, Yang, & Alexa, 2008). These variables were created using the ArcGIS version 10.2 (ESRI, Redlands, CA) and generating a 50-meter circular buffer around the ending latitude and longitude of each monitoring minute. This approach is consistent with one used in a study of adolescents that linked accelerometer data to GPS coordinates (Rodriguez et al., 2012).

Population density was estimated using U.S. Census 2000 data at the block group level and was calculated as the number of persons per square km of area within the 50 m buffer (Berrigan, Pickle, & Dill, 2010). Log of population density with 100 persons/km^2 was used. Street density was created using TIGER street files from the U.S. Census 2000 and was calculated by dividing the total length of the street network within the buffer by the total land area within the buffer. LUM was created using Landuse 2005 from the Office of Geographic Information in Massachusetts (Executive Office for Administration and Finance, 2012). LUM was calculated with an entropy formula (Frank et al., 2005) that estimates the mixture of different types of land use within the buffer (i.e., residential, commercial, recreational, and urban public). The possible values for LUM range from 0 (no diversity) to 1 (maximum diversity). A greenness variable was created within buffers based on the mean normalized difference vegetation index (NDVI), which was measured using Landsat satellite images from 2004 and 2005 (downloaded from the U.S. Geological Survey at http://earthexplorer.usgs.gov) (Bell, Wilson, & Liu, 2008). NDVI values range from +1 (i.e., healthy green vegetation) to −1 (i.e., non-vegetated land cover or water body) (Bell et al., 2008). A walkability index was created within the buffer using LUM, population density, and street density variables (Frank et al., 2005). A normalized distribution (z-score) for each variable was summed to create the walkability index (Frank et al., 2005). Higher values for the walkability index generally indicate that an environment is more conducive to walking and a physically active lifestyle.

Covariates

Participant demographics included age, gender, race (White versus Non-White [including African American or Black, Asian, Native Hawaiian or other Pacific Islander]), and education (undergraduate degree or less versus some graduate courses or graduate degree). Additionally, time of week and time of day variables were created based on accelerometer time stamps since individuals' PA participation may vary during weekdays versus weekend days (Rodriguez et al., 2012). A 4-level time of day variable was created based on minutes occurring overnight (12 am – 5:59 am), morning (6 am – 11:59 am), afternoon (12 pm – 5:59 pm), and evening (6 pm – 11:59 pm) (Lachowycz, Jones, Page, Wheeler, & Cooper, 2011). A variable indicating whether a monitoring minute was on or off a trail (on-trail = 1, off-trail = 0) was also included as a covariate, which was previously described (Tamura et al., 2018).

Variables accounting for temporal data structure of PA

Two variables were created to account for the temporal data structure of the minute-by-minute PA data: monitoring day (i.e., 1-4 days) and "episode" of activity. The episode variable was created using the time stamps from the accelerometer. An episode was considered a continuous activity where there were no more than ten consecutive minutes of missing accelerometer and GPS information. For example, if accelerometer and GPS data were available from 8:00 am to 8:30 am and then were unavailable until 8:40 am, the first time frame would be considered episode 1 and the second starting at 8:40 would be classified as episode 2. In addition, to investigate the sensitivity of the results to different operational definitions for a new episode, we also conducted the analyses by defining a new episode using five minutes of inactivity (rather than 10 minutes) as a criterion. Since the modeling results using the five- and ten-minute criteria for new episodes were comparable, we are presenting results using the ten-minute criterion.

Statistical analysis

Descriptive statistics were calculated for all variables (SAS 9.4 Cary, NC). Associations between built environment variables and MVPA and LVPA were conducted using generalized linear mixed models (GLMM; PROC GLIMMIX in SAS) to handle the multilevel data structure. Minute-by-minute observations (n=60,335) were nested within each episode of activity (level 1), which are nested for each monitoring day (level 2), and which in turn were nested within an individual (level 3). The mixed models specified random intercepts for each of the three levels to account for the clustering of monitoring minutes at each level. For both MVPA and LVPA in age-adjusted models, we fitted a GLMM with four built environment variables (i.e., population density, street density, LUM, and greenness) and age. Subsequently, we fitted a GLMM with the four built environment variables, age, gender, race, education, time of day, time of week, and on versus off trail location in the fully-adjusted models. We estimated two additional fully-adjusted models using the walkability index as an independent variable, since this measure represented the linear combination of population density, street density, and LUM. For each PA outcome, we adjusted for age, gender, race, education, time of day, and on versus off trail location.

Results

Participant characteristics and activity monitoring patterns

Participants' ages ranged from 19 to 78 years of age, with a mean of 44.0 ± 13.0 years (Table 1). Fifty-three percent of 142 participants were women, the majority (72.5%) was white, 56.3% had undergraduate degrees or less and 43.7% had some graduate education or more. On average participants had 3.0 ± 1.1 valid monitoring days out of 4 possible days. Participants wore accelerometers for a daily mean of 864.75 ± 98.40 minutes. Mean accelerometer wear time linked to GPS coordinates was 135.39 ± 59.48 minutes/day. Based on the accelerometer data linked to GPS coordinates, participants engaged in an average of 52.20 ± 31.89 minutes/day of MVPA, an average of 83.19 ± 56.00 minutes/day of LVPA, an average of 42.07 ± 35.89 minutes/day of light PA, and an average of 41.12 ± 29.98 minutes/day of sedentary behavior.

Associations between built environment and MVPA and LVPA

In both age- and fully-adjusted models, population density (OR=0.995, 95% CI=0.993-0.998; OR=0.995, 95% CI=0.995-0.996, respectively) and walkability index (OR=0.952, 95% CI=0.948-0.955; OR=0.969, 95% CI=0.965-0.972, respectively) had statistically significant negative associations with MVPA, yet the effects were weak (Table 2). For example, in both models one-unit increase in log of population density (per 100 persons/km^2) was associated with less than 1% lower odds of engaging MVPA. In both models, street density was also negatively associated with MVPA (OR=0.66, 95% CI = 0.64-0.68; OR=0.69, 95% CI=0.67-0.71, respectively). LUM was negatively associated with MVPA (OR=0.87, 95% CI=0.78-0.97) in the fully-adjusted model. In contrast, the greenness index had statistically significant positive associations with MVPA in both models, yet was attenuated from OR=1.89 (95% CI=1.69-2.11) in the age-adjusted model to OR=1.15 (95% CI=1.03-1.30) in the fully-adjusted model.

Similar patterns of associations between the five built environment variables and LVPA were found in both age- and fully-adjusted models (Table 3). In the fully-adjusted model for LVPA (OR=0.79, 95% CI=0.77-0.81), the negative association for street density was not as strong as the association with MVPA (OR=0.69, 95% CI =0.67-0.71). These estimates represent a 31% lower odds of engaging in MVPA versus a 21% lower odds for LVPA. However, the negative association between LUM and LVPA and positive association between greenness and LVPA were both stronger than the associations found for MVPA (OR=0.81, 95% CI=0.74-0.90; OR=1.25, 95% CI=1.12-1.41, respectively).

Discussion

This study utilized accelerometer and GPS monitoring of 142 adults in Massachusetts to temporally and spatially link built environment exposures to PA. In an analysis that examined relationships between built environment characteristics within 50-meter buffers and minute-by-minute measures of PA, population density, street density, LUM, and a walkability index were negatively associated with both MVPA and LVPA. Alternatively, greenness within these small dynamically buffered areas was positively associated with the both PA outcomes.

The negative associations between population density and MVPA appear to be inconsistent with findings from previous studies using accelerometer and GPS data in adults (Chaix et al., 2016; Troped et al., 2010). In one these studies the authors examined MVPA that occurred within a 1 km buffer around home, which differed from our built environment measures (i.e., 50 m buffer around all GPS-derived locations). Another recent study on GPS data linked to accelerometer based PA data showed that each trip through walking was 1.37 times greater when the origin of the trip was in the fourth quartile (i.e., a highest level of density for all services, including public services, shops, etc.), compared to the first quartile (Chaix et al., 2016). In addition, an earlier analysis of the same sample of adults used in this study, which also took a more home-centric approach, found that residential population density was positively associated with MVPA occurring within 1 km of home and work buffers (Troped et al., 2010). Contrary to the results from these previous studies (Chaix et al., 2016; Troped et al., 2010), our study indicated that participants tended to engage in MVPA in less densely populated areas, as well as locations away from home, yet the magnitude of effects were small.

In the present study street density was also negatively associated with MVPA and LVPA, findings that are not consistent with a recent review of associations of the built environment on walking and bicycling for recreation and transportation within residential areas among all age groups, ranging from children to older adults (Y. Wang, 2015). Overall the authors of this review reported that street connectivity or density was positively associated with transportation and recreational walking and transportation bicycling, yet these built environment measures were restricted to static locations within neighborhoods, parks, and open space (Y. Wang, 2015), not accounting for dynamic nature of PA in relation to environmental exposures, such as ours. In line with our findings, a study examining associations of objectively measured street connectivity with walking patterns among the elderly in Bogota, Columbia, indicated that greater connectivity was negatively associated with walking (Gomez et al., 2010). The researchers concluded that more intersections and busy streets could be related to a perceived risk of traffic accidents among older adults (Gomez et al., 2010). Another recent literature review on the built environment and pedestrian safety documented that higher cross-street density is directly related to pedestrian crashes and traffic volumes are consistently associated with higher pedestrian injuries (Philip Stoker, 2015). A possible explanation for the negative association between street density and PA in the present study could be that participants who were physically active intentionally avoided areas with more intersections and busy streets to engage in activities, such as walking, jogging, and running.

Overall, LUM showed similar negative relationships with both MVPA and LVPA. One review study focusing on adults reported that associations between LUM and recreational PA and walking were generally weak or null (Wendel-Vos, Droomers, Kremers, Brug, & van Lenthe, 2007). Consistent with the present study, a recent study investigating relationships between LUM and transportation PA among Brazilian adults showed that greater LUM was negatively associated with bicycling for transportation (OR=0.52, 95% CI =0.31-0.81) (Hino, Reis, Sarmiento, Parra, & Brownson, 2014). A possible explanation for the negative associations found for LUM in the present study might be that participants prefer to engage in PA in residential neighborhoods that have lower LUM values. These individuals tend to seek quieter, more aesthetically pleasing locations to engage in PA (Tamura et al., 2018). Since we did not collect data on the purpose for PA (e.g., transportation versus recreational) it is difficult to accurately interpret the findings for LUM.

Our finding on positive associations between greenness and MVPA was consistent with a recent study with adult women using GPS monitoring data, (James et al., 2017), and the authors estimated greenness using NDVI. The authors examined relationships between greenness and minute-by-minute PA among women and found that greenness was positively associated with PA, specifically among middle-aged white women with high incomes (James et al., 2017). One general assumption with greenness is that the attractiveness of the scenery (e.g., trees, grass) promotes participation in outdoor physical activities. One potential explanation for the findings from our study may be that well-educated, regularly physically active individuals tend to seek green, open spaces, such as parks and forests to engage in recreational PA (James et al., 2017). Our results support the assumption that individuals may engage in higher intensity of PA (specifically for MVPA outcome) when they are exposed to greenness and open spaces.

The results from the present study indicating that walkability was negatively associated with MVPA were inconsistent with a recent review of built environment studies that indicated high walkability was associated with greater MVPA among adults (Haselwandter et al., 2015). Participants in the present study were recruited from 5 different trails in Massachusetts and reported some regular use of those trails. It is plausible that this sample of adults tended to seek out places to be physically active such as trails and parks where the street density, population density and land use mix values would tend to be lower, especially where the spatial scale used was a relatively small 50 meter buffer around each monitoring minute.

The main strength of the present study is the concurrent use of accelerometer and GPS units to spatially contextualize the precise locations where PA takes place. This dynamic approach addresses an important limitation in past built environment studies, which is the potential spatial mismatch between environmental exposures and PA. The majority of the built environment studies have focused on characterizing the areas around participants' homes, without explicitly determining where PA has occurred. However, individuals' activity is not limited to locations around home (Chaix, Meline, et al., 2013). Approaches and methods that directly link PA behaviors to specific locations has been supported by the field of time geography, relational approaches, and concept of activity space (Perchoux et al., 2013; Rainham et al., 2010).

Several limitations of this study include the sample characteristics and aspects of the GPS and accelerometer measures. Participants were physically active, recruited at the five trails, mostly white and resided in urban and suburban communities in Massachusetts. Their PA levels appear to be higher than the general U.S. population of adults. Thus, the results may therefore not be generalizable to folks who are non-trail users, less active, more racially and ethnically diverse, of lower education, and residing in more urban settings. Another study limitation is that the data analyzed only included monitoring minutes with GPS coordinates linked to accelerometer counts. It is likely that GPS monitoring was impeded in areas with heavy tree canopy, and tall buildings, such as densely developed areas of Boston. This is due to attenuation of signals from GPS satellites, which could bias the estimated associations. In our study, we were unable to address a selective mobility bias, meaning that individuals who visit certain locations throughout the day-to-day activities have specific characteristics, such as behavioral, demographic, psychosocial characteristics, which influence individual's PA (Chaix, Kestens, et al., 2013). This bias could impact our estimates. Additionally, participants only wore a GPS up to 4 days, which is less than the currently recommended duration of monitoring period at least 12-14 days (Holliday, Howard, Emch, Rodriguez, Rosamond, et al., 2017; Zenk, Matthews, Kraft, & Jones, 2018). Lastly, as this study is cross-sectional, we cannot infer any causality between the built environment and PA.

Conclusions

Use of accelerometer data linked to geographic coordinates through GPS allowed us to more precisely investigate relationships between objectively measured built environment variables and minute-by-minute PA. Four built environment variables (population density, street density, LUM and walkability index) were negatively associated with PA, in contrast to numerous prior studies. A potential explanation for the contradictory findings may be that adults who frequently used trails and generally engaged in relatively high levels of PA, sought out less populated environments with lower street density and less commercial activity (Philip Stoker, 2015). Also, other previous studies tended to focus on static, home-centric locations for environmental exposure assessments, rather than dynamically linking PA to environmental exposures via GPS monitoring. . Further research should consider analyzing data at the minute-by-minute level to explicitly link PA to the immediate environmental exposures to minimize the spatial mismatch between exposures and these behaviors. This line of research could enhance our understanding of the complex relationships between the built environment and different types of recreational and utilitarian PA.

What Does This Article Add?

Concurrent application of accelerometer and GPS monitoring to examine immediate built environmental exposures in relation to physical activity have been conducted in children, but not many for adults. However, little is known about how GPS-derived built environment variables are associated with a minute-by-minute physical activity, particularly among adults. This study contributes to the scant scientific literature to address a key limitation in the past built environment research, the potential spatial mismatch between environmental exposures and PA . We used both accelerometer and GPS units to spatially quantify the precise locations where PA occurs. Street density and LUM were negatively associated with PA outcomes in contrast to numerous studies that have focused on fixed residential buffers. Greenness was positively associated with the PA outcomes – consistent with previous studies in adults. Further research is needed to investigate places where objectively measured physical activity takes place and associations with built environment exposures at those locations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

The authors thank Ms. Yunfan Li and Dr. Bruce Craig from the Department of Statistics, Purdue University, for their feedback on statistical modeling approaches.

Funding

This study was supported by the Robert Wood Johnson Foundation, the Active Living Research Program and additional funding from the American Heart Association.

References

2018 Physical Activity Guidelines Advisory Committee. (2018). 2018 Physical Activity Guidelines Advisory Committee Scientific Report. Washington, D.C.

Bell JF, Wilson JS, & Liu GC (2008). Neighborhood greenness and 2-year changes in body mass index of children and youth. Am J Prev Med, 35(6), 547. [PubMed: 19000844]

Berrigan D, Pickle LW, & Dill J (2010). Associations between street connectivity and active transportation. Int J Health Geogr, 9, 20. doi:1476-072X-9-20 [pii] 10.1186/1476-072X-9-20 [PubMed: 20412597]

Cerin E, Cain KL, Oyeyemi AL, Owen N, Conway TL, Cochrane T, … Sallis JF (2016). Correlates of Agreement between Accelerometry and Self-reported Physical Activity. Med Sci Sports Exerc, 48(6), 1075–1084. doi:10.1249/MSS.0000000000000870 [PubMed: 26784274]

Chaix B (2018). Mobile Sensing in Environmental Health and Neighborhood Research. Annu Rev Public Health, 39, 367–384. doi:10.1146/annurev-publhealth-040617-013731 [PubMed: 29608869]

Chaix B, Kestens Y, Duncan DT, Brondeel R, Meline J, El Aarbaoui T, … Merlo J. (2016). A GPS-Based Methodology to Analyze Environment-Health Associations at the Trip Level: Case-Crossover

Analyses of Built Environments and Walking. Am J Epidemiol, 184(8), 570–578. doi:10.1093/aje/kww071 [PubMed: 27659779]

Chaix B, Kestens Y, Perchoux C, Karusisi N, Merlo J, & Labadi K (2013). An interactive mapping tool to assess individual mobility patterns in neighborhood studies. Am J Prev Med, 43(4), 440–450. doi:S0749-3797(12)00466-7 [pii] 10.1016/j.amepre.2012.06.026

Chaix B, Meline J, Duncan S, Merrien C, Karusisi N, Perchoux C, … Kestens Y. (2013). GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? Health Place, 21, 46–51. doi:S1353-8292(13)00009-9 [pii] 10.1016/j.healthplace.2013.01.003 [PubMed: 23425661]

Community Preventive Services Task Force. (2016). Physical Activity: Built Environment Approaches Combining Transportation System Interventions with Land Use and Environmental Design. Retrieved from https://www.thecommunityguide.org/

Crouter SE, DellaValle DM, Haas JD, Frongillo EA, & Bassett DR (2013). Validity of ActiGraph 2-regression model, Matthews cut-points, and NHANES cut-points for assessing free-living physical activity. J Phys Act Health, 10(4), 504–514. doi:2011-0169 [pii] [PubMed: 22975460]

Dunton GF, Berrigan D, Ballard-Barbash R, Graubard BI, & Atienza AA (2008). Social and physical environments of sports and exercise reported among adults in the American Time Use Survey. Prev Med doi:S0091-7435(08)00348-4 [pii] 10.1016/j.ypmed.2008.07.001

Evenson KR, Wen F, Hillier A, & Cohen DA (2013). Assessing the contribution of parks to physical activity using global positioning system and accelerometry. Med Sci Sports Exerc, 45(10), 1981–1987. doi:10.1249/MSS.0b013e318293330e [PubMed: 23531716]

Executive Office for Administration and Finance. (2012). Office of Geographic Information (MassGIS). Retrieved from http://www.mass.gov/anf/research-and-tech/it-serv-and-support/application-serv/office-of-geographic-information-massgis/

Frank LD, Schmid TL, Sallis JF, Chapman J, & Saelens BE (2005). Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. Am J Prev Med, 28(2 Suppl 2), 117–125. [PubMed: 15694519]

Gomez LF, Parra DC, Buchner D, Brownson RC, Sarmiento OL, Pinzon JD, … Lobelo F. (2010). Built environment attributes and walking patterns among the elderly population in Bogota. Am J Prev Med, 38(6), 592–599. doi:S0749-3797(10)00176-5 [pii] 10.1016/j.amepre.2010.02.005 [PubMed: 20494235]

Haselwandter EM, Corcoran MP, Folta SC, Hyatt R, Fenton M, & Nelson ME (2015). The built environment, physical activity, and aging in the United States: a state of the science review. J Aging Phys Act, 23(2), 323–329. doi:10.1123/japa.2013-0151 [PubMed: 24911115]

Hino AA, Reis RS, Sarmiento OL, Parra DC, & Brownson RC (2014). Built environment and physical activity for transportation in adults from Curitiba, Brazil. J Urban Health, 91(3), 446–462. doi:10.1007/s11524-013-9831-x [PubMed: 24096625]

Holliday KM, Howard AG, Emch M, Rodriguez DA, & Evenson KR (2017). Are buffers around home representative of physical activity spaces among adults? Health & Place, 45, 181–188. doi:10.1016/j.healthplace.2017.03.013 [PubMed: 28391129]

Holliday KM, Howard AG, Emch M, Rodriguez DA, Rosamond WD, & Evenson KR (2017). Deriving a GPS Monitoring Time Recommendation for Physical Activity Studies of Adults. Med Sci Sports Exerc, 49(5), 939–947. doi:10.1249/MSS.0000000000001190 [PubMed: 28009791]

James P, Hart JE, Hipp JA, Mitchell JA, Kerr J, Hurvitz PM, … Laden F. (2017). GPS-Based Exposure to Greenness and Walkability and Accelerometry-Based Physical Activity. Cancer Epidemiol Biomarkers Prev, 26(4), 525–532. doi:10.1158/1055-9965.EPI-16-0925 [PubMed: 28196848]

Krenn PJ, Titze S, Oja P, Jones A, & Ogilvie D (2011). Use of global positioning systems to study physical activity and the environment: a systematic review. Am J Prev Med, 41(5), 508–515. doi:S0749-3797(11)00546-0 [pii] 10.1016/j.amepre.2011.06.046 [PubMed: 22011423]

Lachowycz K, Jones AP, Page AS, Wheeler BW, & Cooper AR (2011). What can global positioning systems tell us about the contribution of different types of urban greenspace to children's physical activity? Health Place, 18(3), 586–594. doi:S1353-8292(12)00007-X [pii] 10.1016/j.healthplace.2012.01.006

Lindsey G, Wilson J, Yang JA, & Alexa C (2008). Urban Greenways, Trail Characteristics and Trail Use: Implications for Design. Journal of Urban Design, 13, 53–79.

Matthew CE (2005). Calibration of accelerometer output for adults. Med Sci Sports Exerc, 37(11 Suppl), S512–522. [PubMed: 16294114]

Matthews CE, Chen KY, Freedson PS, Buchowski MS, Beech BM, Pate RR, & Troiano RP (2008). Amount of time spent in sedentary behaviors in the United States, 2003-2004. Am J Epidemiol, 167(7), 875–881. doi:kwm390 [pii] 10.1093/aje/kwm390 [PubMed: 18303006]

Perchoux C, Chaix B, Cummins S, & Kestens Y (2013). Conceptualization and measurement of environmental exposure in epidemiology: accounting for activity space related to daily mobility. Health Place, 21, 86–93. doi:S1353-8292(13)00011-7 [pii] 10.1016/j.healthplace.2013.01.005 [PubMed: 23454664]

Philip Stoker AG-C, Meleckidzedeck Khayesi, Wilson Odero, Martin N. Mwangi, Margie Peden, and Reid Ewing. (2015). Pedestrian safety and the built environment: A review of the risk factors. Journal of Planning Literature, 1–16.

Rainham D, McDowell I, Krewski D, & Sawada M (2010). Conceptualizing the healthscape: Contributions of time geography, location technologies and spatial ecology to place and health research. Social Science & Medicine, 70(5), 668–676. [PubMed: 19963310]

Rodriguez DA, Cho GH, Evenson KR, Conway TL, Cohen D, Ghosh-Dastidar B, … Lytle LA. (2012). Out and about: association of the built environment with physical activity behaviors of adolescent females. Health Place, 18(1), 55–62. doi:S1353-8292(11)00160-2 [pii] 10.1016/j.healthplace. 2011.08.020 [PubMed: 21945085]

Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, & Kerr J (2006). An ecological approach to creating active living communities. Annu Rev Public Health, 27, 297–322. doi:10.1146/ annurev.publhealth.27.021405.102100 [PubMed: 16533119]

Tamura K, Langerman SD, Ceasar JN, Andrews MR, Agrawal M, & Powell-Wiley TM (2019). Neighborhood Social Environment and Cardiovascular Disease Risk. Current Cardiovascular Risk Reports, 13(4). doi:ARTN 7 10.1007/s12170-019-0601-5

Tamura K, Wilson JS, Puett RC, Klenosky DB, Harper WA, & Troped PJ (2018). Accelerometer and GPS Analysis of Trail Use and Associations With Physical Activity. Journal of Physical Activity & Health, 15(7), 523–530. doi:10.1123/jpah.2016-0667 [PubMed: 29580165]

Troiano RP, Berrigan D, Dodd KW, Masse LC, Tilert T, & McDowell M (2008). Physical activity in the United States measured by accelerometer. Med Sci Sports Exerc, 40(1), 181–188. doi:10.1249/ mss.0b013e31815a51b3 [PubMed: 18091006]

Troped PJ, Wilson JS, Matthews CE, Cromley EK, & Melly SJ (2010). The built environment and location-based physical activity. Am J Prev Med, 38(4), 429–438. doi:S0749-3797(10)00012-7 [pii] 10.1016/j.amepre.2009.12.032 [PubMed: 20307812]

Wendel-Vos W, Droomers M, Kremers S, Brug J, & van Lenthe F (2007). Potential environmental determinants of physical activity in adults: a systematic review. Obes Rev, 8(5), 425–440. doi:OBR370 [pii] 10.1111/j.1467-789X.2007.00370.x [PubMed: 17716300]

Wang Y, C CK., Ng WY, Leung TM. (2015). A review on the effects of physical built environment attributes on enhancing walking and cycling activity levels within residential neighborhoods. Cities, 50, 1–15.

Zenk SN, Matthews SA, Kraft AN, & Jones KK (2018). How many days of global positioning system (GPS) monitoring do you need to measure activity space environments in health research? Health & Place, 51, 52–60. doi:10.1016/j.healthplace.2018.02.004 [PubMed: 29549754]

Table 1.

Participants' demographic, physical activity, and built environment characteristics (N=142)

Age, n (%)	
19-29 years	19 (13.5)
30-39 years	37 (26.2)
40-49 years	36 (25.5)
50-59 years	32 (22.7)
≥ 60 years	17 (12.1)
Gender, n (%)	
Female	75 (53.2)
Male	67 (47.2)
Race, n (%)	
White	103 (72.5)
Non-white[a]	39 (27.6)
Education, n (%)	
Undergraduate degree or less	80 (56.3)
Some graduate or graduate degree	62 (43.7)
Physical activity, mean min per day (SD)	
Moderate-to-vigorous physical activity	52.20 (31.89)
Light-to-vigorous physical activity	83.19 (56.00)
Light physical activity	42.07 (35.89)
Sedentary	41.12 (29.98)
Built environment, mean (SD)	
Population density per sq. km	3374.45 (2645.71)
Street density per sq. km	16.24 (3.67)
Land use mix	0.18 (0.09)
Greenness	0.20 (0.10)
Walkability index	0.71 (2.97)

Note:

[a]African-American or Black, Asian, Native Hawaiian or other Pacific Islander

Table 2.

Associations between built environment variables and moderate-to-vigorous physical activity (MVPA) (N =60,335)

	MVPA			
	Age-adjusted[b]		Fully-adjusted[c]	
Built environment variables[a]	**OR**	**95% CI**	**OR**	**95% CI**
Log of population density (100 people per sq. km)	0.995[+]	0.993, 0.998	0.995[+]	0.995, 0.996
Street density (10 km per sq. km)[b]	0.658[+]	0.641, 0.675	0.691[+]	0.672, 0.710
LUM	0.939	0.847, 1.042	0.869[*]	0.781, 0.967
Greenness	1.887[+]	1.688, 2.109	1.154[*]	1.026, 1.297
Walkability index	0.952[+]	0.948, 0.955	0.969[+]	0.965, 0.972

Note:

[a]Built environment characteristics within 50 m buffer around each minute of activity.

[b]Age adjusted model included four built environment variables (or walkability index) and age.

[c]Fully adjusted model included four built environment variables (or walkability index) and covariates.

[+]$p<.0001$;

[*]$p<.05$

Table 3.

Associations between built environment variables and light-to-vigorous physical activity (LVPA) (N =60,335)

	LVPA			
	Age-adjusted[b]		Fully-adjusted[c]	
Built environment variables[a]	**OR**	**95% CI**	**OR**	**95% CI**
Log of population density (100 people per sq. km)	0.995[+]	0.994, 0.995	0.999[+]	0.998, 0.999
Street density (10 km per sq. km)	0.744[+]	0.726, 0.763	0.787[+]	0.768, 0.807
LUM	0.821[+]	0.744, 0.906	0.812[+]	0.735, 0.898
Greenness	1.833[+]	1.640, 2.049	1.252[+]	1.115, 1.406
Walkability index	0.964[+]	0.961, 0.967	0.979[+]	0.976, 0.982

Note:

[a]Built environment characteristics within 50 m buffer around each minute of activity.

[b]Age adjusted model included four built environment variables (or walkability index) and age.

[c]Fully adjusted model included four built environment variables (or walkability index) and covariates.

[+]p<.0001;

[*]p<.05