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GPS-based activity space exposure to greenness and walkability is associated with increased accelerometer-based physical activity

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Abstract

Introduction: Built and natural environments may provide opportunities for physical activity. However, studies are limited by primarily using residential addresses to define exposure and self-report to measure physical activity. We quantified associations between global positioning

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CRediT authorship contribution statement
Oriol Marquet: Conceptualization, Data curation, Writing – original draft. **Jana A. Hirsch:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jacqueline Kerr:** Writing – review & editing, Funding acquisition. **Marta M. Jankowska:** . **Jonathan Mitchell:** . **Jaime E. Hart:** . **Francine Laden:** . **J. Aaron Hipp:** Conceptualization, Writing – original draft, Project administration. **Peter James:** Conceptualization, Methodology, Formal analysis, Writing – original draft.

Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material
Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2022.107317.

systems (GPS)-based activity space measures of environmental exposure and accelerometer-based physical activity.

Methods: Using a nationwide sample of working female adults (N = 354), we obtained seven days of GPS and accelerometry data. We created Daily Path Area activity spaces using GPS data and linked these activity spaces to spatial datasets on walkability (EPA Smart Location Database at the Census block group level) and greenness (satellite vegetation at 250 m resolution). We utilized generalized additive models to examine nonlinear associations between activity space exposures and accelerometer-derived physical activity outcomes adjusted for demographic characteristics, socioeconomic factors, and self-rated health.

Results: Higher activity space walkability was associated with higher levels of moderate-vigorous physical activity, and higher activity space greenness was associated with greater numbers of steps per week. No strong relationships were observed for sedentary behavior or light physical activity. Highest levels of moderate-vigorous physical activity were observed for participants with both high walkability and high greenness in their activity spaces.

Conclusion: This study contributes evidence that higher levels of physical activity occur in environments with more dense, diverse, and well-connected built environments, and with higher amounts of vegetation. These data suggest that urban planners, landscape architects, and policy makers should implement and evaluate environmental interventions to encourage higher levels of physical activity.

1. Introduction

Physical inactivity is a major behavioral risk factor for cancer, cardiovascular disease, diabetes, hypertension, and other chronic diseases (Sallis et al., 2016), yet only 53% of US men and 47% of US women reach physical activity guidelines (Ward et al., 2008). Research, informed by the ecosocial model (Krieger, 2005), has highlighted the potential role of environmental contextual factors to provide opportunities for physical activity (Zhang et al., 2016; McNeill et al., 2006; James et al., 2015; Sallis et al., 2012).

Two features that have emerged as potential facilitators of physical activity are the built and natural environment. The built environment, provides opportunities or barriers to routinely walk and be physically active (Handy et al., 2002; Cdc, 2011). Characteristics of the built environment such as population density, land use mix, connectivity and design have been repeatedly found associated with higher accessibility levels (Leslie et al., 2007; Frank et al., 2010), being able to walk to a higher number of daily destinations and thus with higher population levels of physical activity (Feng et al., 2010). Walkability measures are commonly used to encompass these built environment features and have been linked to transport-related physical activity (Hirsch et al., 2014; Hirsch et al., 2014), particularly utilitarian walking (Cerin et al., 2007). People living in environments with more destinations within walking distance walk more often (Villanueva et al., 2014; Norman et al., 2013; Marquet and Miralles-Guasch, 2015; Marquet and Miralles-Guasch, 2016) and for longer distances (Millward et al., 2013; Owen et al., 2007). Within the natural environment, exposure to high levels of vegetation and green space has also been associated with increased physical activity (James et al., 2015; Almanza et al., 2012; Lachowycz et al., 2012; Vich et al., 2021). Studies have found that exercise facilities such as fitness areas or children play areas within green spaces, together with enjoyable scenery and seeing other active people, may encourage physical activity (Potwarka et al., 2008; Kerr et al., 2012; Mitra et al., 2015; Wendel-Vos et al., 2007; McMorris et al., 2015; Dewulf et al., 2016; Cohen et al., 2012; DelCampo et al., 2017; Marquet et al., 2019a,2019b). Green spaces may also encourage leisure- and transportation-related physical activity, as green spaces provide both a walking/cycling destination and venue for play and exercise (Bedimo-Rung et al., 2005) although findings are inconsistent (Schipperijn et al., 2013; Ord et al., 2013).

In the past two decades, studies have incorporated device-based methods to assess physical activity (e.g. pedometers, accelerometers, other biosensors) (Hajna et al., 2015). These tools offer high-resolution, accurate measurements of movement (Troiano et al., 2014). Use of accelerometry data is starting to provide new evidence on the association between walkability and physical activity worldwide (Sallis et al., 2016; Vanhelst et al., 2013), in dense urban spaces (Rundle et al., 2016), among particular demographic groups (King et al., 2011; Hirsch et al., 2016; Rodríguez et al., 2012), and across several domains (Yang et al., 2014; Marquet and Hipp, 2019;March(7):20–26.; Marquet et al., 2020). Use of device-based measures is also advancing in green space studies (James et al., 2015; Halonen et al., 2020), where accelerometers have extended evidence linking greenness with increased physical activity among children (Almanza et al., 2012; Lachowycz et al., 2012; Ward et al., 2016) and adults (Dewulf et al., 2016). However, research has struggled with small sample sizes and mixed findings.

Studies trying to assess environmental exposures have relied on administrative boundaries (Leal and Chaix, 2011; Foster and Hipp, 2011), which may introduce significant measurement error by assuming participants stay within these boundaries (Spielman and Yoo, 2009) and introducing well-documented spatial bias such as the NEAP (Kwan, 2018) or UGCoP (Kwan, 2018). In the past, many studies have centered measurements around a participant's residential address (Sarmiento et al., 2010; van Loon et al., 2014; Hwang et al., 2016), failing to acknowledge spaces participants encounter throughout their daily lives (Hirsch et al., 2016,2014; Vich et al., 2017), and making important assumptions about size and shape of areas around an address to consider (James et al., 2014). Overall, these traditional geographic measures of neighborhood have failed to accurately capture environmental exposures which has led some to suggest that the literature needs to move beyond notions of contextual influence that rely on using such specific fixed locations (Kwan, 2018; Sheller and Urry, 2006). GPS technology can overcome some of these limitations by offering a dynamic measure of the environmental context (Jankowska et al., 2014). GPS-based measures can generate "activity spaces" that represent the area within which people move or travel in the course of their daily activities. GPS-based activity spaces include all movements during the day for all purposes and with any mode of transport (Hirsch et al., 2014); (Marwa et al., 2021), and they can later be paired with GIS data to measure environmental exposures (Ward et al., 2016; Chaix et al., 2013; Kerr et al., 2012). Recently, researchers have used the triad of GPS location, GIS exposure, and sensor-based physical activity outcomes to create a transdisciplinary field coined as "Spatial Energetics (Marquet et al., 2020; James et al., 2016). Linking behavioral and spatial data facilitates the examination of location and physical activity at precise spatiotemporal scales (James et al., 2016). While this nascent work shows promise, additional research is needed using larger samples and examining greenspace. There also exists a gap for examining nonlinear relationships, which could potentially account for changes in physical activity that might occur once certain thresholds or minimum values of environmental features are present (Moudon et al., 2006; Sugiyama et al., 2012). Similarly, limited environmental variability may impact measured associations between the environment and physical activity.

This study fills a gap in the literature by examining device-based measured physical activity with GPS-based activity space measures of greenness and walkability. With participants located throughout four different study sites across the US, we also maximized exposure variability and context. We hypothesized that higher levels of greenness and walkability within a participant's activity space would be associated with higher intensities of physical activity.

2. Methods

2.1. Population

A sample of female participants was recruited from four sites from the National Cancer Institute (NCI)-funded Transdisciplinary Research in Energetics and Cancer (TREC) initiative (Patterson et al., 2013). As described elsewhere (James et al., 2017), the sample was made up of working adults (University of California, San Diego (UCSD) and Washington University in St. Louis (WUSTL)), members of the prospective Nurses' Health Study II cohort (Harvard University (Harvard)), and breast cancer survivors (University of Pennsylvania (UPenn)). Eligibility criteria for this study were: female, 21–75 years old, self-reported BMI 21.0–39.9, ability to ambulate unassisted, not pregnant or breast-feeding, and willing to wear monitoring devices for seven days. Site-specific eligibility criteria included: currently employed full or part-time (WUSTL) and previously diagnosed with breast cancer (UPenn). Furthermore, 17% of the UCSD sample was comprised of confirmed breast cancer survivors. The Harvard sample was selected from participants in the Nurses Health Study II with a BMI less than 40, and was sampled to evenly represent varying population densities and all Census regions of the US (African Americans were oversampled). For the Harvard sample, 120 recruitment letters were sent out and 91 participants provided data for this analysis. Institutional review boards at each university approved the protocol, and all participants provided informed consent.

Participants were enrolled over 12 months in 2012–2013, completed baseline surveys, and were instructed to wear an Actigraph GT3X+ accelerometer and a Qstarz BT1000X GPS device on the hip during all waking hours (except when showering, bathing, or swimming) for seven consecutive days. Participants removed devices at night to charge the GPS device.

All data in these analyses were centrally pooled and uniformly processed at UCSD.

2.2. Accelerometer data

Accelerometer data were screened manually for wear time compliance. We collected raw accelerometer data at 30 Hertz and aggregated as counts in one-minute epochs. Wear time was assessed using the Choi algorithm in Actilife 6.11, which assesses 90 consecutive minutes of zero counts as non-wear allowing for up to two minutes of nonzero counts to remove artifactual movement (Choi et al., 2011). Data were manually screened by trained personnel to identify valid days. Data were excluded if there were fewer than five days of data with 600 min per day of wear time or fewer than four days with 3000 min of total accelerometer wear time (Troiano et al., 2008). Counts per minute (CPM) from the vertical axis of the accelerometer were used to derive steps and physical activity intensities. We employed the Troiano physical activity cutpoints for sedentary (≤99 CPM), light (100–2019 CPM), and moderate or vigorous physical activity (≥2020 CPM) (Troiano et al., 2008). We also used the report of total steps recorded by the accelerometer.

2.3. Global positioning systems data

Qstarz GPS devices logged location coordinates, distance, speed, elevation, and time. Qstarz validation studies have reported accuracy of 3 m, and all GPS devices were evaluated for this level of accuracy before deployment. We configured devices to record location and time data at 15 s intervals.

2.4. Activity spaces

We analyzed GPS location data, aggregated by participant, using Python 2.7.2 and ArcPy for ArcGIS 10.4. We examined Daily Path Areas (DPA) adapted from previous literature (Hirsch et al., 2014; Zenk et al., 2011; Starnes, 2012) by creating 200 m merged buffers for all of a participant's GPS data (see Fig. 1). DPA are considered as the best approach to analyze the cumulative exposure experienced through daily mobility at the street level (Hirsch et al., 2014; Vich et al., 2017). To assess optimal activity space calculation (Hirsch et al., 2016; Patterson and Farber, 2015), sensitivity analyses were performed using two additional activity space approaches (standard deviation ellipse (SDE) and minimum convex polygon (MCP)) (see Supplemental Fig. 1). SDE measure the directional distribution of a series of points and are usually used to observe the normal range of spatial motion for an individual (Zenk et al., 2011; Starnes, 2012; Sherman et al., 2005; Rainham et al., 2010; Newsome et al., 1998). MCP, sometimes referred to as "home ranges", represents the smallest polygon that contains all GPS points, with the outermost points serving as vertices. Detailed methods for creating activity space measures have been published previously (Zenk et al., 2011; Sherman et al., 2005; Fan and Khattak, 2008). Because mean walkability and greenness values for participants across different activity space types were highly correlated (Spearman's $\rho > 0.76$ for walkability $\rho > 0.91$ for greenness), results are presented only for DPAs.

2.5. Spatial datasets and exposures

2.5.1. Greenness—Normalized difference vegetation index (NDVI) values estimate vegetation, or greenness, in an area. Reflected sunlight from satellite-measured red and near-infrared bands of the light spectrum are converted to generate NDVI values with a range of −1.0 to 1.0 (larger values indicating higher vegetation density) (Kriegler et al., 1968). We used Moderate-resolution Imaging Spectroradiometer (MODIS) data deployed on NASA's Terra satellite. Imagery from July 2012 approximated the greenness levels at the time of data collection (Carroll et al., 2004). Average NDVI values from 250 m resolution satellite data were calculated for each activity space. Fig. 1 shows a participant's activity space linked to greenness.

2.5.2. Walkability—Average area-weighted walkability values were calculated for activity spaces by averaging the sum of walkability values that fall within the activity space areas. Each activity space was linked to a walkability index from the US Environmental Protection Agency (EPA) Smart Location Database (SLD). SLD provides nationwide geographic data on 90 attributes summarizing built environment characteristics at the Census Block Group level (Ramsey and Bell, 2014). The walkability index was compiled using: Gross population density (people/acre) on unprotected land; Street intersection density (weighted, with auto-oriented intersections eliminated); and Land Use Diversity (based on mix of retail, office, service, industrial, entertainment, education, healthcare, and public administration employment). We created Z-scores (mean of 0, standard deviation of 1) for each measure across all Block Groups in the US and summed these Z-scores to estimate a walkability index for each Census Block Group. Higher walkability index indicates a more walkable neighborhood. All spatial exposures were calculated and appended to activity spaces using ArcGIS v10.6.1 (Red-lands, CA).

2.5.3. Demographic characteristics—Survey data included information on age (years), race (White; Black; Other), marital status (Married; Never Married, Divorced, Separated, or Widowed), educational attainment (Less than College; College; Graduate Degree), household annual income from all sources (<$50 K per year; $50 K–$69 K per year; $70 K per year; Missing or Refused to Answer), employment status (Full Time; Part Time; Homemaker, Unemployed, Unable to Work; Retired), and self-rated health status (Poor, Fair, Good; Very Good, Excellent).

2.6. Statistical analysis

We used generalized additive models to estimate relationships between activity space walkability or greenness and weekly-averaged physical activity, adjusted for demographic characteristics. We built models including both greenness and walkability to assess potential confounding between environmental features. We also ran single-exposure models, but results were similar to mutually adjusted models (Supplemental Fig. 2) so we present mutually-adjusted models. We used natural splines to test for deviations from linearity and estimate thresholds. We compared Akaike's Information Criteria (AIC) values for linear versus nonlinear models. In addition, we explored interactions between greenness and walkability, to understand whether the relationship between greenness and physical activity differed according to levels of walkability, and vice versa. Data were analyzed in R (version 3.4.0).

3. Results

3.1. Population characteristics

Of the 354 participants, the majority were White (79%), married (71%), worked full time (51%), and made over $70 K/year (46%) (Table 1). The average age of participants was 55.3 years. A minority of participants walked or biked to work (9%), and just over half rated their health as very good or excellent (54%). The majority of data was collected in the spring (36.4%) and winter (29.7%), while 24.7% of data were collected in the fall and 9.2% of data were collected in the summer months.

3.2. Main effects models

3.2.1. Sedentary behavior—Fig. 2a and b show fully-adjusted spline models for sedentary behavior, mutually adjusted for both greenness and walkability within 200 m DPA activity spaces. There was no relationship between activity space greenness and sedentary behavior ($p = 0.39$). There was a statistically significant ($p = 0.047$) relationship between activity space walkability and sedentary behavior. Specifically, for walkability below 0 there was no relationship between walkability and sedentary behavior; however, from 0 to 1, higher levels of walkability were related to lower levels of sedentary behavior, and above 1, higher levels of walkability were associated with greater sedentary behavior.

3.2.2. Light physical activity—The relationship between activity space greenness and light physical activity was positive and linear but did not reach statistical significance ($p = 0.07$, Fig. 2c and d). Alternatively, walkability was not associated with light physical activity.

3.2.3. Moderate-vigorous physical activity—Models for both activity space measures demonstrated positive linear associations with accelerometer measured moderate-vigorous physical activity (MVPA) (Fig. 2e and f) although only walkability reached statistical significance. Greenness was positively associated with moderate-vigorous physical activity (a 0.1 increase in activity space NDVI was associated with a 0.8 (95% CI −0.6, 2.2) minute per day increase in moderate-vigorous physical activity), although this failed to reach statistical significance ($p = 0.13$). A one-unit increase in walkability was associated with statistically significant 11.7 min/day (95% CI 1.8, 21.7) higher moderate-vigorous physical activity.

3.2.4. Steps—Activity space greenness was positively associated with average number of steps per day in spline models ($p = 0.0051$) (Fig. 2g). Association between greenness and steps was strongest for NDVI measures below 0.5 and attenuated somewhat at levels above 0.5. There was no relationship between activity space walkability and steps ($p = 0.32$) (Fig. 2h).

3.2.5. Interactions between greenness and walkability—Analyses examining interactions between activity space greenness and walkability (Fig. 3a–d) revealed no evidence of interactions for sedentary behavior (Fig. 3a) or light physical activity (Fig. 3b). There was evidence of a linear interaction (Fig. 3c) ($p = 0.03$) between greenness and walkability for moderate-vigorous physical activity, where levels of moderate-vigorous physical activity were highest among those who had activity spaces with both high walkability and high greenness. There was also evidence of nonlinear interactions between greenness and walkability for steps (Fig. 3d) ($p = 0.03$), where the highest step counts were observed for participants with activity spaces with the highest greenness and walkability; however, these relationships were not consistent across all levels of greenness and walkability.

4. Discussion

Using data from a sample of women at four sites across the United States who provided a week of GPS and accelerometer data, we observed that participants whose activity spaces had higher levels of walkability also had higher levels of moderate-vigorous physical activity. Furthermore, higher activity-space greenness was associated with a greater number of steps per week. No strong relationships were observed for activity space exposures and sedentary behavior nor light physical activity. We found evidence of interactions between activity space greenness and walkability for moderate-vigorous physical activity, where the highest levels of moderate-vigorous physical activity were observed for participants who had activity spaces containing both high walkability and high greenness. Interactions between activity space greenness and walkability on the associations with steps were inconsistent.

Previous research has reported discordance between exposures measured at the residential and activity space-level (Chaix, 2018; Hurvitz and Moudon, 2012). These inconsistencies have prompted calls for increased examinations of relationships between non-residential environments and physical activity (Hirsch et al., 2014; Holliday et al., 2017). Shifting from a restrictive focus on residential environments to activity space measures allowed us to account for environmental exposures in the diverse places visited by participants (Chaix et al., 2017). Thus, we were able to include daily physical activity that takes place away from residential neighborhoods (Marquet et al., 2020; Hurvitz et al., 2014; Holliday et al., 2017; Kestens et al., 2018).

Our findings suggest that individuals may obtain higher levels of physical activity in walkable environments. While existent literature had already extensively explored this relationship at the neighborhood and residential scale (Hajna et al., 2015; Hwang et al., 2016; Sundquist et al., 2011; Lee et al., 2016; Hoehner et al., 2011; Kondo et al., 2009; Duncan et al., 2016), only a handful of articles has explored it at the activity space level (Chaix, 2018). Our results are consistent with Rundle's et al. (Rundle et al., 2016) which also used activity spaces and accelerometer-based measures of physical activity in New York City. This work showed a positive relationship between walkability and moderate physical activity. Using similar methods, Hirsch et al. (2016) found consistent, although statistically non-significant, associations between density of destinations within participants activity spaces and physical activity in a group of community-dwelling older adults from Vancouver. Others have found that a change in walkability within an activity space can lead to increased physical activity (Andersen et al., 2017). Using self-reported measures of physical activity, Howell et al. (2017) found a positive and significant relationship between walkability and participants' transportation physical activity. These associations were stronger when walkability was measured at the activity space level, compared with only around the residential environment. Furthermore, the negative association between walkability and sedentary time in areas that reach a minimum threshold of walkability is consistent with theories advocating for minimum densities and compact development in order to generate physical activity or active transport (James et al., 2017; Christiansen et al., 2016; Cerin et al., 2017).

Our findings also suggest that higher greenness levels may be associated with daily steps or light physical activity. Among other studies using greenness at the activity space level, our results are consistent with Jansen et al. (2017), who studied natural environments and physical activity, and with Kang et al. (2017) who examined the association of recreational walking with the amount of land park/trails within activity spaces. They contrast, however, with the insignificant associations found by Zenk et al. (2011). Our positive association between greenness and average steps also contradicts van Heeswijck et al. (2015) who found a negative association between activity space-NDVI and walking for transport. Other studies exploring the association between either momentary or activity space exposure to greenness and physical activity outcomes have generally found a positive correlation (Almanza et al., 2012; James et al., 2017; Chaix et al., 2016). Inconsistencies may be partially explained by exclusion of walkability in combination with greenness. In that context, our results add important evidence that the interaction between greenness and walkability might be positively associated with moderate to vigorous physical activity and average number of steps (Shuvo et al., 2021). This is one of the first studies to jointly consider these effects, especially within activity spaces.

Our analyses were limited by the use of a sample of older women who were working adults, members of a prospective cohort of nurses, and breast cancer survivors, impacting generalizability, especially to men, who may interact differently with their environments. Second, GIS data on walkability and greenness may not capture all relevant environmental features (e.g., sidewalk availability, vegetation species, park amenities) that might promote activity. The use of NDVI as a proxy of the amount of accessible greenspace might be affected by the presence of large but inaccessible green areas. Additionally, different data sources (e.g. Landsat 8 or Sentinel-2) may provide higher spatial or spectral resolution that may lead to different results. Third, several data source features and processing decisions may have led to measurement error. Participants' activity during the one recorded week may not be representative of their complete routine behavior (Zenk et al., 2018). Similarly, our findings may suffer from selective daily mobility bias, or confounding by intrapersonal characteristics which arises when individual preferences simultaneously lead individuals to visit certain locations and also drive the behaviors conducted in those locations (Schipperijn et al., 2014; Carlson et al., 2015; Meseck et al., 2016). If this were true, the relationship we found would be overestimated; however, the degree to which this is true is unknown as we do not have detailed information from participants on why they visit specific locations.

Despite these limitations, our analyses contribute an understanding of the environmental characteristics of locations where individuals are active. Other substantial strengths include device-based, high spatiotemporal resolution GPS-based measures of activity spaces and accelerometer-based measures of physical activity in a relatively large sample. These measures were joined with high-quality data on greenness and walkability collected uniformly nationwide. While we were unable to characterize the urbanicity, history, or other contextual factors of the participant locations, the broad geographic sample and uniform measurement of exposures increases generalizability across geographic contexts.

Standardized approaches across multiple study sites enabled pooling of consistently collected data. We also explored nonlinear relationships, allowing us to explore potential threshold relationships. This is one of the first studies to examine activity spaces and physical activity using nonlinear approaches. Our observed evidence of interactions between walkability and greenness might be relevant for future analyses. Overall, this study adds evidence to the literature showing that higher levels of physical activity occur in environments that have higher walkability and amounts of vegetation. Along with other research, our findings might inform implementation and evaluation of interventions that increase neighborhood walkability and greenness. Our findings suggest that policies to increase density, diversity, and connectedness of the built environment may increase physical activity. In addition, this study indicates that interventions to plant vegetation should focus on doing so in areas where walkability is high to maximize opportunities for physical activity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

Almanza E, Jerrett M, Dunton GF, Seto E, Ann PM, 2012. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. Heal Place. 18 (1), 46–54. 10.1016/j.healthplace.2011.09.003.

Andersen HB, Christiansen LB, Klinker CD, Ersbøll AK, Troelsen J, Kerr J, Schipperijn J, 2017. Increases in use and activity due to urban renewal: effect of a natural experiment. Am. J. Prev. Med 53 (3), e81–e87. 10.1016/j.amepre.2017.03.010. [PubMed: 28495219]

Bedimo-Rung AL, Mowen AJ, Cohen DA, 2005. The significance of parks to physical activity and public health. A conceptual model. Am. J. Prev. Med 28 (2S2), 159–168. 10.1016/j.ampre.2004.10.024. [PubMed: 15694524]

Carlson JA, Jankowska MM, Meseck Kristin, Godbole Suneeta, Natarajan Loki, Raab Fredric, Demchak Barry, Patrick Kevin, Kerr Jacqueline, 2015. Validity of PALMS GPS scoring of active and passive travel compared with SenseCam. Med. Sci. Sports Exerc 47 (3), 662–667. 10.1249/MSS.0000000000000446. [PubMed: 25010407]

Carroll ML, DiMiceli CM, Sohlberg RA, 2004. Townshend JRG. 250m MODIS Normalized Difference Vegetation Index, Published online 2004.

CDC, 2011. Impact of the Built Environment on Health. <https://www.cdc.gov/nceh/publications/factsheets/impactofthebuiltenvironmentonhealth.pdf>.

Cerin E, Leslie E, du Toit L, Owen N, Frank L, 2007. Destinations that matter: associations with walking for transport. Health Place. 13 (3), 713–724. 10.1016/j.healthplace.2006.11.002. [PubMed: 17239654]

Cerin E, Nathan A, van Cauwenberg J, Barnett DW, Barnett A, 2017. The neighbourhood physical environment and active travel in older adults: a systematic review and meta-analysis. Int. J. Behav. Nutr. Phys. Act 14 (1) 10.1186/s12966-017-0471-5.

Chaix B, 2018. Mobile sensing in environmental health and neighborhood research. Annu. Rev. Public Health 39 (1), 367–384. 10.1146/annurev-publhealth-040617-013731. [PubMed: 29608869]

Chaix B, Meline J, Duncan S, Merrien C, Karusisi N, Perchoux C, Lewin A, Labadi K, Kestens Y, 2013. GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? Heal Place. 21, 46–51.

Chaix B, Kestens Y, Duncan DT, Brondeel R, Méline J, El Aarbaoui T, Pannier B, 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), 579–589. 10.1093/aje/kww071. [PubMed: 27698005]

Chaix B, Duncan D, Vallée J, Vernez-Moudon A, Benmarhnia T, Kestens Y, 2017. The, "Residential" effect fallacy in neighborhood and health studies: formal definition, empirical identification, and correction. Epidemiology 28 (6), 789–797. 10.1097/EDE.0000000000000726. [PubMed: 28767516]

Choi L, Liu Z, Matthews CE, Buchowski MS, 2011. Validation of accelerometer wear and nonwear time classification algorithm. Med. Sci. Sports Exerc 43 (2), 357–364. 10.1249/MSS.0b013e3181ed61a3. [PubMed: 20581716]

Christiansen LB, Cerin E, Badland H, et al. , 2016. International comparisons of the associations between objective measures of the built environment and transport-related walking and cycling : IPEN adult study. J. Transp. Heal 3, 467–478. 10.1016/j.jth.2016.02.010.

Cohen DA, Marsh T, Williamson S, Golinelli D, McKenzie TL, 2012. Impact and cost-effectiveness of family Fitness Zones: a natural experiment in urban public parks. Heal Place. 18 (1), 39–45. 10.1016/j.healthplace.2011.09.008.

DelCampo C, Tutte V, Bermudez G, Parra DC, 2017. Impact on area level physical activity following the implementation of fitness zones in montevideo uruguay. J. Phys. Act Heal 1–19. doi:10.1123/jpah.2016-0394.

Dewulf B, Neutens T, Van Dyck D, De Bourdeaudhuij I, Broekx S, Beckx C, Van de Weghe N, 2016. Associations between time spent in green areas and physical activity among late middle-aged adults. Geospat. Health 11 (3) 10.4081/gh.2016.411.

Duncan D, Méline J, Kestens Y, Day K, Elbel B, Trasande L, Chaix B, 2016. Walk score, transportation mode choice, and walking among french adults: a GPS, accelerometer, and mobility survey study. Int. J. Environ. Res. Public Health 13 (6), 611. 10.3390/ijerph13060611. [PubMed: 27331818]

Fan Y, Khattak AJ, 2008. Urban form, individual spatial footprints, and travel: examination of space-use behavior. Transp. Res. Rec. J. Transp. Res. Board 2082 (1), 98–106. 10.3141/2082-12.

Feng J, Glass TA, Curriero FC, Stewart WF, Schwartz BS, 2010. The built environment and obesity: a systematic review of the epidemiologic evidence. Heal Place. 16 (2), 175–190. 10.1016/j.healthplace.2009.09.008.

Foster K, Hipp JA, 2011. Defining neighborhood boundaries for social measurement: advancing social work research. Soc. Work Res 35, 25–35. 10.1093/swr/35.1.25.

Frank LD, Sallis JF, Saelens BE, Leary L, Cain K, Conway TL, Hess PM, 2010. The development of a walkability index: application to the neighborhood quality of life study. Br. J. Sports Med 44 (13), 924–933. 10.1136/bjsm.2009.058701. [PubMed: 19406732]

Hajna S, Ross NA, Brazeau A-S, Bélisle P, Joseph L, Dasgupta K, 2015. Associations between neighbourhood walkability and daily steps in adults: a systematic review and meta-analysis. BMC Public Health 15 (1), 768. 10.1186/s12889-015-2082-x. [PubMed: 26260474]

Halonen JI, Pulakka A, Pentti J, Kallio M, Koskela S, Kivimäki M, Kawachi I, Vahtera J, Stenholm S, 2020. Cross-sectional associations of neighbourhood socioeconomic disadvantage and greenness with accelerometer-measured leisure-time physical activity in a cohort of ageing workers. BMJ Open. 10 (8), e038673. 10.1136/bmjopen-2020-038673.

Handy SL, Boarnet MG, Ewing R, Killingsworth RE, 2002. How the built environment affects physical activity. Am. J. Prev. Med 23 (2), 64–73. [PubMed: 12133739]

Hirsch JA, Roux AVD, Moore KA, Evenson KR, Rodriguez DA, 2014. Change in walking and body mass index following residential relocation: the multi-ethnic study of atherosclerosis. Am. J. Public Health 104 (3), 49–56. 10.2105/AJPH.2013.301773.

Hirsch JA, Winters M, Clarke P, McKay H, 2014. Generating GPS activity spaces that shed light upon the mobility habits of older adults: a descriptive analysis. Int. J. Health Geogr 13 (1) 10.1186/1476-072X-13-51.

Hirsch JA, Moore KA, Clarke PJ, Rodriguez DA, Evenson KR, Brines SJ, Zagorski MA, Diez Roux AV, 2014. Changes in the built environment and changes in the amount of walking over time: longitudinal results from the multi-ethnic study of Atherosclerosis. Am. J. Epidemiol 180 (8), 799–809. 10.1093/aje/kwu218. [PubMed: 25234431]

Hirsch JA, Winters M, Ashe MC, Clarke PJ, McKay HA, 2016. Destinations that older adults experience within their GPS activity spaces: relation to objectively measured physical activity. Environ. Behav 48 (1), 55–77. 10.1177/0013916515607312. [PubMed: 26783370]

Hoehner CM, Handy S, Yan Y, Blair SN, Berrigan D, 2011. Association between neighborhood walkability, cardiorespiratory fitness and body-mass index. Soc. Sci. Med 73 (12), 1707–1716. 10.1016/j.socscimed.2011.09.032. [PubMed: 22030212]

Holliday KM, Howard AG, Emch M, Rodríguez DA, Evenson KR, 2017. Are buffers around home representative of physical activity spaces among adults? Heal Place. 45 (March), 181–188. 10.1016/j.healthplace.2017.03.013.

Holliday KM, Howard AG, Emch M, Rodríguez DA, Rosamond WD, Evenson KR, 2017. Where are adults active? An examination of physical activity locations using GPS in five US cities. J. Urban Heal 94 (4), 459–469. 10.1007/s11524-017-0164-z.

Howell NA, Farber S, Widener MJ, Booth GL, 2017. Residential or activity space walkability: what drives transportation physical activity? J. Transp. Heal 7 (May), 160–171. 10.1016/j.jth.2017.08.011.

Hurvitz PM, Moudon AV, 2012. Home versus nonhome neighborhood: quantifying differences in exposure to the built environment. Am. J. Prev. Med 42 (4), 411–417. 10.1016/j.amepre.2011.11.015. [PubMed: 22424255]

Hurvitz PM, Moudon AV, Kang B, Fesinmeyer MD, Saelens BE, 2014. How far from home? The locations of physical activity in an urban U.S. setting. Prev. Med. (Baltim.) 69, 181–186. 10.1016/j.ypmed.2014.08.034.

Hwang LD, Hurvitz PM, Duncan GE, 2016. Cross sectional association between spatially measured walking bouts and neighborhood walkability. Int. J. Environ. Res. Public Health 13 (4), 1–11. 10.3390/ijerph13040412.

James P, Berrigan D, Hart JE, Aaron Hipp J, Hoehner CM, Kerr J, Major JM, Oka M, Laden F, 2014. Effects of buffer size and shape on associations between the built environment and energy balance. Heal Place. 27, 162–170.

James P, Banay RF, Hart JE, Laden F, 2015. A review of the health benefits of greeness. Curr. Epidemiol. Rep 2 (2), 131–142. 10.1007/s40471-015-0043-7. [PubMed: 26185745]

James P, Banay RF, Hart JE, Laden F, 2015. A review of the health benefits of greenness. Curr. Epidemiol. Rep 2 (2), 131–142. 10.1007/s40471-015-0043-7. [PubMed: 26185745]

James P, Jankowska M, Marx C, Hart JE, Berrigan D, Kerr J, Hurvitz PM, Hipp JA, Laden F, 2016. “Spatial Energetics”: integrating data from GPS, accelerometry, and GIS to address obesity and inactivity. Am. J. Prev. Med 51 (5), 792–800. 10.1016/j.amepre.2016.06.006. [PubMed: 27528538]

James P, Hart JE, Hipp JA, Mitchell JA, Kerr J, Hurvitz PM, Glanz K, Laden F, 2017. GPS-based exposure to greenness and walkability and accelerometry-based physical activity. Cancer Epidemiol. Biomark. Prev 26 (4), 525–532. 10.1158/1055-9965.EPI-16-0925.

Jankowska MM, Schipperijn J, Kerr J, 2014. A framework for using GPS data in physical activity and sedentary behavior studies. Exe. Sport Sci. Rev 43(1), 48–56. doi:10.1249/JES.0000000000000035.

Jansen FM, Ettema DF, Kamphuis CBM, Pierik FH, Dijst MJ, 2017. How do type and size of natural environments relate to physical activity behavior? Heal Place. 46 (May), 73–81. 10.1016/j.healthplace.2017.05.005.

Kang B, Moudon AV, Hurvitz PM, Saelens BE, 2017. Differences in behavior, time, location, and built environment between objectively measured utilitarian and recreational walking. Transp. Res. Part D Transp. Environ 57 (October), 185–194. 10.1016/j.trd.2017.09.026.

Kerr J, Marshall S, Godbole S, Neukam S, Crist K, Wasilenko K, Golshan S, Buchner D, 2012. The relationship between outdoor activity and health in older adults using GPS. Int. J. Environ. Res. Public Health 9 (12), 4615–4625. 10.3390/ijerph9124615. [PubMed: 23330225]

Kerr J, Rosenberg D, Frank L, 2012. The role of the built environment in healthy aging: community design, physical activity, and health among older adults. J. Plan Lit 27 (1), 43–60. 10.1177/0885412211415283.

Kestens Y, Thierry B, Shareck M, Steinmetz-Wood M, Chaix B, 2018. Integrating activity spaces in health research: comparing the VERITAS activity space questionnaire with 7-day GPS tracking and prompted recall. Spat. Spatiotemporal. Epidemiol 25, 1–9. 10.1016/j.sste.2017.12.003. [PubMed: 29751887]

King AC, Sallis JF, Frank LD, Saelens BE, Cain K, Conway TL, Chapman JE, Ahn DK, Kerr J, 2011. Aging in neighborhoods differing in walkability and income: associations with physical activity and obesity in older adults. Soc. Sci. Med 73 (10), 1525–1533. 10.1016/j.socscimed.2011.08.032. [PubMed: 21975025]

Kondo K, Lee JS, Kawakubo K, Kataoka Y, Asami Y, Mori K, Umezaki M, Yamauchi T, Takagi H, Sunagawa H, Akabayashi A, 2009. Association between daily physical activity and neighborhood environments. Environ. Health Prev. Med 14 (3), 196–206. 10.1007/s12199-009-0081-1. [PubMed: 19568848]

Krieger N, 2005. Embodiment: a conceptual glossary for epidemiology. J. Epidemiol. Community Health 59 (5), 350–355. 10.1136/jech.2004.024562. [PubMed: 15831681]

Kriegler F, Malila W, Nalepka R, Richardson W, 1968. Preprocessing transformations and their effects on multispectral recognitio. In: Proceedings of the Sixth International Symposium on Remote Sensing of Environment, pp. 97–131.

Kwan M-P, 2018. The neighborhood effect averaging problem (NEAP): an elusive confounder of the neighborhood effect. Int. J. Environ. Res. Public Health 15 (9), 1841. 10.3390/ijerph15091841. [PubMed: 30150510]

Kwan MP, 2018. The limits of the neighborhood effect: contextual uncertainties in geographic, environmental health, and social science research. Ann. Am. Assoc. Geogr 108 (6), 1482–1490. 10.1080/24694452.2018.1453777.

Lachowycz K, Jones AP, Page AS, Wheeler BW, Cooper AR, 2012. What can global positioning systems tell us about the contribution of different types of urban greenspace to children's physical activity? Heal Place. 18 (3), 586–594. 10.1016/j.healthplace.2012.01.006.

Leal C, Chaix B, 2011. The influence of geographic life environments on cardiometabolic risk factors: a systematic review, a methodological assessment and a research agenda. Obes. Rev 12 (3), 217–230. 10.1111/j.1467-789X.2010.00726.x. [PubMed: 20202135]

Lee L-L, Kuo Y-L, Chan E-Y, 2016. The association between built environment attributes and physical activity in East Asian adolescents: a systematic review. Asia-Pacific J. Public Heal 28 (3), 206–218. 10.1177/1010539516628174.

Leslie E, Coffee N, Frank L, Owen N, Bauman A, Hugo G, 2007. Walkability of local communities: using geographic information systems to objectively assess relevant environmental attributes. Heal Place. 13 (1), 111–122. 10.1016/j.healthplace.2005.11.001.

Marquet O, Hipp JA, 2019. Worksite built environment and objectively measured physical activity while at work. an analysis using perceived and objective walkability and greenness. J. Environ. Health March (7), 20–26.

Marquet O, Hipp JA, Alberico C, et al. , 2019a. How does park use and physical activity differ between childhood and adolescence? A focus on gender and raceethnicity. J. Urban Heal 96 (5), 692–702. 10.1007/s11524-019-00388-8.

Marquet O, Miralles-Guasch C, 2015. Neighbourhood vitality and physical activity among the elderly: the role of walkable environments on active ageing in Barcelona, Spain. Soc. Sci. Med 135, 24–30. 10.1016/j.socscimed.2015.04.016. [PubMed: 25939073]

Marquet O, Floyd MF, James P, Glanz K, Jennings V, Jankowska MM, Kerr J, Hipp JA, 2020. Associations between worksite walkability, greenness, and physical activity around work. Environ. Behav 52 (2), 139–163. 10.1177/0013916518797165.

Marquet O, Aaron Hipp J, Alberico C, Huang J-H, Fry D, Mazak E, Lovasi GS, Floyd MF, 2019b. Park use preferences and physical activity among ethnic minority children in low-income neighborhoods in New York City. Urban For. Urban Green. 38, 346–353. 10.1016/j.ufug.2019.01.018.

Marquet O, Miralles-Guasch C, 2016. Introducing urban vitality as a determinant of children's healthy mobility habits: a focus on activity engagement and physical activity. Child Geogr. 14 (6), 656–669. 10.1080/14733285.2016.1157572.

Marwa WL, Radley D, Davis S, McKenna J, Griffiths C, 2021. Exploring factors affecting individual GPS-based activity space and how researcher-defined food environments represent activity space, exposure and use of food outlets. Int. J. Health Geogr 20 (1), 34. 10.1186/s12942-021-00287-9. [PubMed: 34320996]

McMorris O, Villeneuve PJ, Su J, Jerrett M, 2015. Urban greenness and physical activity in a national survey of Canadians. Environ. Res 137, 94–100. 10.1016/j.envres.2014.11.010. [PubMed: 25527908]

McNeill LH, Kreuter MW, Subramanian SV, 2006. Social environment and physical activity: a review of concepts and evidence. Soc. Sci. Med 63 (4), 1011–1022. 10.1016/j.socscimed.2006.03.012. [PubMed: 16650513]

Meseck K, Jankowska MM, Schipperijn J, Natarajan L, Godbole S, Carlson J, Takemoto M, Crist K, Kerr J, 2016. Is missing geographic positioning system data in accelerometry studies a problem, and is imputation the solution? Geospat. Health 11 (2). 10.4081/gh.2016.403.

Millward H, Spinney J, Scott D, 2013. Active-transport walking behavior: destinations, durations, distances. J. Transp. Geogr 28, 101–110. 10.1016/j.jtrangeo.2012.11.012.

Mitra R, Siva H, Kehler M, 2015. Walk-friendly suburbs for older adults? Exploring the enablers and barriers to walking in a large suburban municipality in Canada. J. Aging. Stud 35, 10–19. 10.1016/j.jaging.2015.07.002. [PubMed: 26568210]

Moudon AV, Lee C, Cheadle AD, Garvin C, Johnson D, Schmid TL, Weathers RD, Lin L, 2006. Operational definitions of walkable neighborhood: theoretical and empirical insights. J. Phys. Act. Health 3 (s1), S99–S117. [PubMed: 28834523]

Newsome TH, Walcott WA, Smith PD, 1998. Urban activity spaces: Illustrations and application of a conceptual model for integrating the time and space dimensions. Transportation (Amst). 25 (4), 357–377. 10.1023/A:1005082827030.

Norman GJ, Carlson JA, O'Mara S, Sallis JF, Patrick K, Frank LD, Godbole SV, 2013. Neighborhood preference, walkability and walking in overweight/obese men. Am. J. Health Behav 37 (2), 277–282. 10.5993/AJHB.37.2.15. [PubMed: 23026109]

Ord K, Mitchell R, Pearce J, 2013. Is level of neighbourhood green space associated with physical activity in green space? Int. J. Behav. Nutr. Phys. Act 10 (1), 127. 10.1186/1479-5868-10-127. [PubMed: 24219824]

Owen N, Cerin E, Leslie E, duToit L, Coffee N, Frank LD, Bauman AE, Hugo G, Saelens BE, Sallis JF, 2007. Neighborhood walkability and the walking behavior of Australian adults. Am. J. Prev. Med 33 (5), 387–395. [PubMed: 17950404]

Patterson RE, Colditz GA, Hu FB, Schmitz KH, Ahima RS, Brownson RC, Carson KR, Chavarro JE, Chodosh LA, Gehlert S, Gill J, Glanz K, Haire-Joshu D, Herbst KL, Hoehner CM, Hovmand PS, Irwin ML, Jacobs LA, James AS, Jones LW, Kerr J, Kibel AS, King IB, Ligibel JA, Meyerhardt JA, Natarajan L, Neuhouser ML, Olefsky JM, Proctor EK, Redline S, Rock CL, Rosner B, Sarwer DB, Schwartz JS, Sears DD, Sesso HD, Stampfer MJ, Subramanian SV, Taveras EM, Tchou J, Thompson B, Troxel AB, Wessling-Resnick M, Wolin KY, Thornquist MD, 2013. The 2011–2016 Transdisciplinary Research on Energetics and Cancer (TREC) initiative: rationale and design. Cancer Causes Control 24 (4), 695–704. 10.1007/s10552-013-0150-z. [PubMed: 23378138]

Patterson Z, Farber S, 2015. Potential path areas and activity spaces in application: a review. Transp. Rev 35 (6), 679–700. 10.1080/01441647.2015.1042944.

Potwarka LR, Kaczynski AT, Flack AL, 2008. Places to play: association of park space and facilities with healthy weight status among children. J. Commun. Health 33 (5), 344–350. 10.1007/s10900-008-9104-x.

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. Soc. Sci. Med 70 (5), 668–676. 10.1016/j.socscimed.2009.10.035. [PubMed: 19963310]

Ramsey K, Bell A, 2014. Smart location database: version 2.0. Environ. Prot. Agency EPA 1–52.

Rodríguez DA, Cho G-H, Evenson KR, Conway TL, Cohen D, Ghosh-Dastidar B, Pickrel JL, Veblen-Mortenson S, Lytle LA, 2012. Out and about: association of the built environment with physical activity behaviors of adolescent females. Health Place. 18 (1), 55–62. [PubMed: 21945085]

Rundle AG, Sheehan DM, Quinn JW, Bartley K, Eisenhower D, Bader MMD, Lovasi GS, Neckerman KM, 2016. Using GPS data to study neighborhood walkability and physical activity. Am. J. Prev. Med 50 (3), e65–e72. 10.1016/j.amepre.2015.07.033. [PubMed: 26558700]

Sallis JF, Floyd MF, Rodríguez DA, Saelens BE, 2012. Role of built environments in physical activity, obesity, and cardiovascular disease. Circulation 125 (5), 729–737. 10.1161/CIRCULATIONAHA.110.969022. [PubMed: 22311885]

Sallis JF, Cerin E, Conway TL, Adams MA, Frank LD, Pratt M, Salvo D, Schipperijn J, Smith G, Cain KL, Davey R, Kerr J, Lai P-C, Mitáš J, Reis R, Sarmiento OL, Schofield G, Troelsen J, Van Dyck D, De Bourdeaudhuij I, Owen N, 2016. Physical activity in relation to urban environments in 14 cities worldwide: a cross-sectional study. The Lancet 387 (10034), 2207–2217.

Sarmiento OL, Schmid TL, Parra DC, Díaz-del-Castillo A, Gómez LF, Pratt M, Jacoby E, Pinzón JD, Duperly J, 2010. Quality of life, physical activity, and built environment characteristics among colombian adults. J. Phys. Act Health 7 (s2), S181–S195. [PubMed: 20702906]

Schipperijn J, Bentsen P, Troelsen J, Toftager M, Stigsdotter UK, 2013. Associations between physical activity and characteristics of urban green space. Urban For. Urban Green 12 (1), 109–116. 10.1016/j.ufug.2012.12.002.

Schipperijn J, Kerr J, Duncan S, Madsen T, Klinker CD, Troelsen J, 2014. Dynamic accuracy of GPS receivers for use in health research: a novel method to assess gps accuracy in real-world settings. Front Public Heal. 2 (March), 1–8. 10.3389/fpubh.2014.00021.

Sheller M, Urry J, 2006. The new mobilities paradigm. Environ. Plan. A 38 (2), 207–226. 10.1068/a37268.

Sherman JE, Spencer J, Preisser JS, Gesler WM, Arcury T., a., 2005. A suite of methods for representing activity space in a healthcare accessibility study. Int. J. Health Geogr 4, 24. 10.1186/1476-072X-4-24. [PubMed: 16236174]

Shuvo FK, Mazumdar S, Labib SM, 2021. Walkability and greenness do not walk together: Investigating associations between greenness and walkability in a large metropolitan city context. Int. J. Environ. Res. Public Health 18 (9), 4429. 10.3390/ijerph18094429. [PubMed: 33919473]

Spielman S, Yoo E, 2009. The spatial dimensions of neighborhood effects. Soc. Sci. Med 68 (6), 1098–1105. 10.1016/j.socscimed.2008.12.048. [PubMed: 19167802]

Starnes HA, 2012. Tests and development of perceived and objective built environment measures for physical activity research. Published online 2012. <http://linksource.ebsco.com/ls.941a0f3a-fc44–412f-81a4–365a06658f2f.false/linking.aspx?&sidOVID:psycdb&idpmid:&iddoi:&issn0419–4217&isbn9781267753328&volume74&issue3-B(E)&spageNo&pagesNoPaginationSpecified&date2013&titleDissertationAbstr>.

Sugiyama T, Neuhaus M, Cole R, Giles-Corti B, Owen N, 2012. Destination and route attributes associated with adults' walking: a review. Med. Sci. Sport Excer 44 (7), 1275–1286. 10.1249/MSS.0b013e318247d286.

Sundquist K, Eriksson U, Kawakami N, Skog L, Ohlsson H, Arvidsson D, 2011. Neighborhood walkability, physical activity, and walking behavior: the Swedish Neighborhood and Physical Activity (SNAP) study. Soc. Sci. Med 72 (8), 1266–1273. 10.1016/j.socscimed.2011.03.004. [PubMed: 21470735]

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

Troiano RP, McClain JJ, Brychta RJ, Chen KY, 2014. Evolution of accelerometer methods for physical activity research. Br. J. Sports Med 48 (13), 1019–1023. 10.1136/bjsports-2014-093546. [PubMed: 24782483]

van Heeswijck T, Paquet C, Kestens Y, Thierry B, Morency C, Daniel M, 2015. Differences in associations between active transportation and built environmental exposures when expressed using different components of individual activity spaces. Health Place. 33, 195–202. 10.1016/j.healthplace.2015.03.003. [PubMed: 25862996]

van Loon J, Frank L, Nettlefold L, Naylor P-J, 2014. Youth physical activity and the neighbourhood environment: examining correlates and the role of neighbourhood definition. Soc. Sci. Med 104, 107–115. 10.1016/j.socscimed.2013.12.013. [PubMed: 24581068]

Vanhelst J, Béghin L, Salleron J, Ruiz JR, Ortega FB, De Bourdeaudhuij I, Molnar D, Manios Y, Widhalm K, Vicente-Rodriguez G, Mauro B, Moreno LA, Sjöström M, Castillo MJ, Gottrand F, 2013. A favorable built environment is associated with better physical fitness in European adolescents. Prev. Med. (Baltim) 57 (6), 844–849. 10.1016/j.ypmed.2013.09.015.

Vich G, Marquet O, Miralles-Guasch C, 2017. Suburban commuting and activity spaces: using smartphone tracking data to understand the spatial extent of travel behaviour. Geogr. J 183 (4), 426–439. 10.1111/geoj.12220.

Vich G, Delclòs X, Maciejewska M, Marquet O, Schipperjin J, Miralles-Guasch C, 2021. Contribution of park visits to daily physical activity levels among older adults: evidence using GPS and accelerometery data. Urban For. Urban Green 2021 (63), 127225. 10.1016/j.ufug.2021.127225.

Villanueva K, Knuiman M, Nathan A, Giles-Corti B, Christian H, Foster S, Bull F, 2014. The impact of neighborhood walkability on walking: does it differ across adult life stage and does neighborhood buffer size matter? Health Place. 25, 43–46. [PubMed: 24239702]

Ward JS, Duncan JS, Jarden A, Stewart T, 2016. The impact of children’s exposure to greenspace on physical activity, cognitive development, emotional wellbeing, and ability to appraise risk. Heal Place. 40, 44–50. 10.1016/j.healthplace.2016.04.015.

Ward B, Clarke T, Freeman G, Schiller J, 2008. Early release of selected estimates based on data from the January–September 2014 National Health Interview Survey 2010(April/17), 53–58. <http://www.cdc.gov/nchs/data/nhis/earlyrelease/earlyrelease201503_08.pdf>.

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. 10.1111/j.1467-789X.2007.00370.x. [PubMed: 17716300]

Yang L, Hipp JA, Adlakha D, Marx CM, Tabak RG, Brownson RC, 2014. Choice of commuting mode among employees: do home neighborhood environment, worksite neighborhood environment, and worksite policy and supports matter? J. Transp. Heal 2 (2), 212–218. 10.1016/j.jth.2015.02.003.

Zenk SN, Schulz AJ, Matthews SA, Odoms-Young A, Wilbur JoEllen, Wegrzyn L, Gibbs K, Braunschweig C, Stokes C, 2011. Activity space environment and dietary and physical activity behaviors: a pilot study. Heal Place. 17 (5), 1150–1161.

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. [PubMed: 29549754]

Zhang J, Brackbill D, Yang S, Becker J, Herbert N, Centola D, 2016. Support or competition? How online social networks increase physical activity: a randomized controlled trial. Prev. Med. Rep 4, 453–458. 10.1016/j.pmedr.2016.08.008. [PubMed: 27617191]

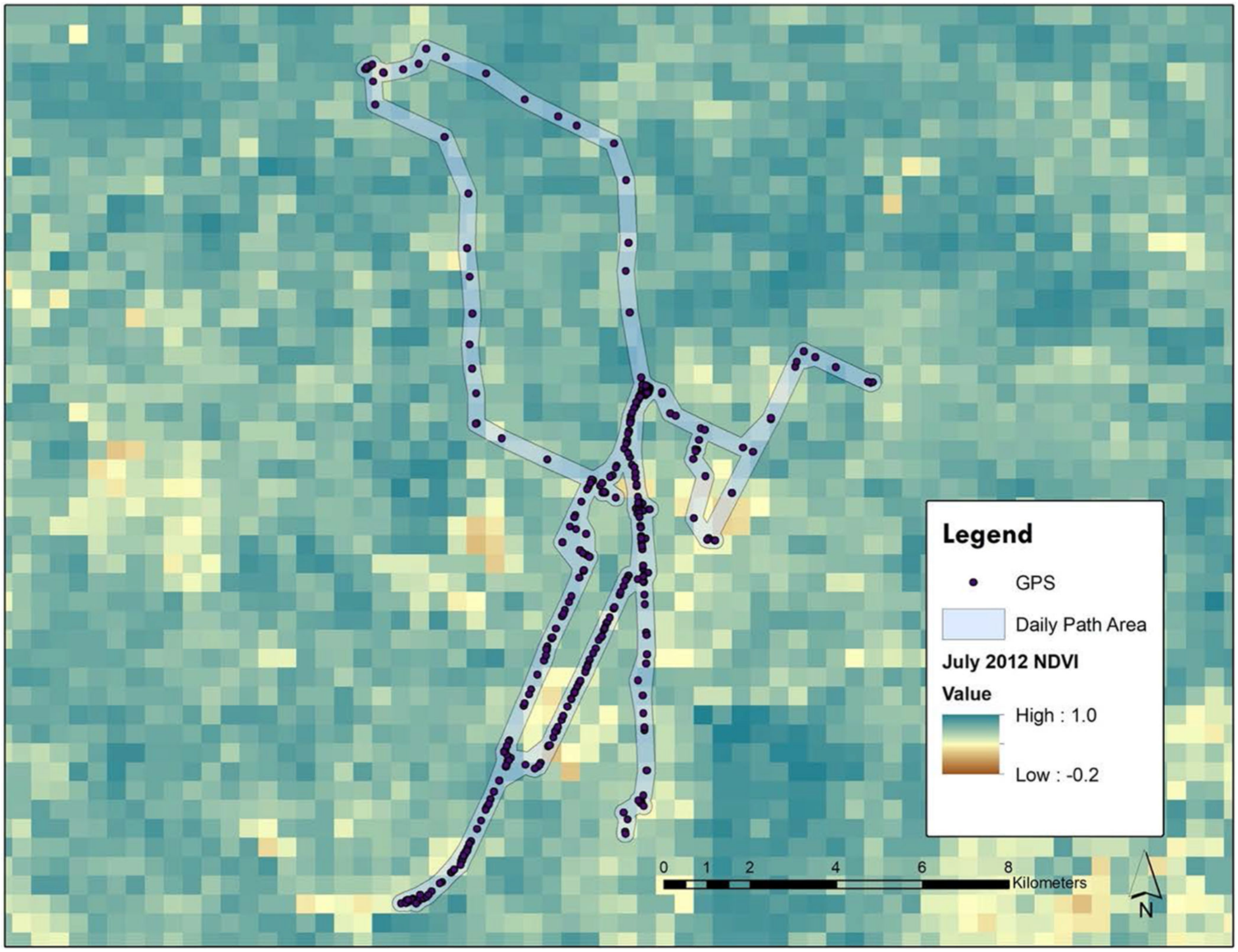

Fig. 1.
Example of GPS data, daily path area activity spaces, and greenness.

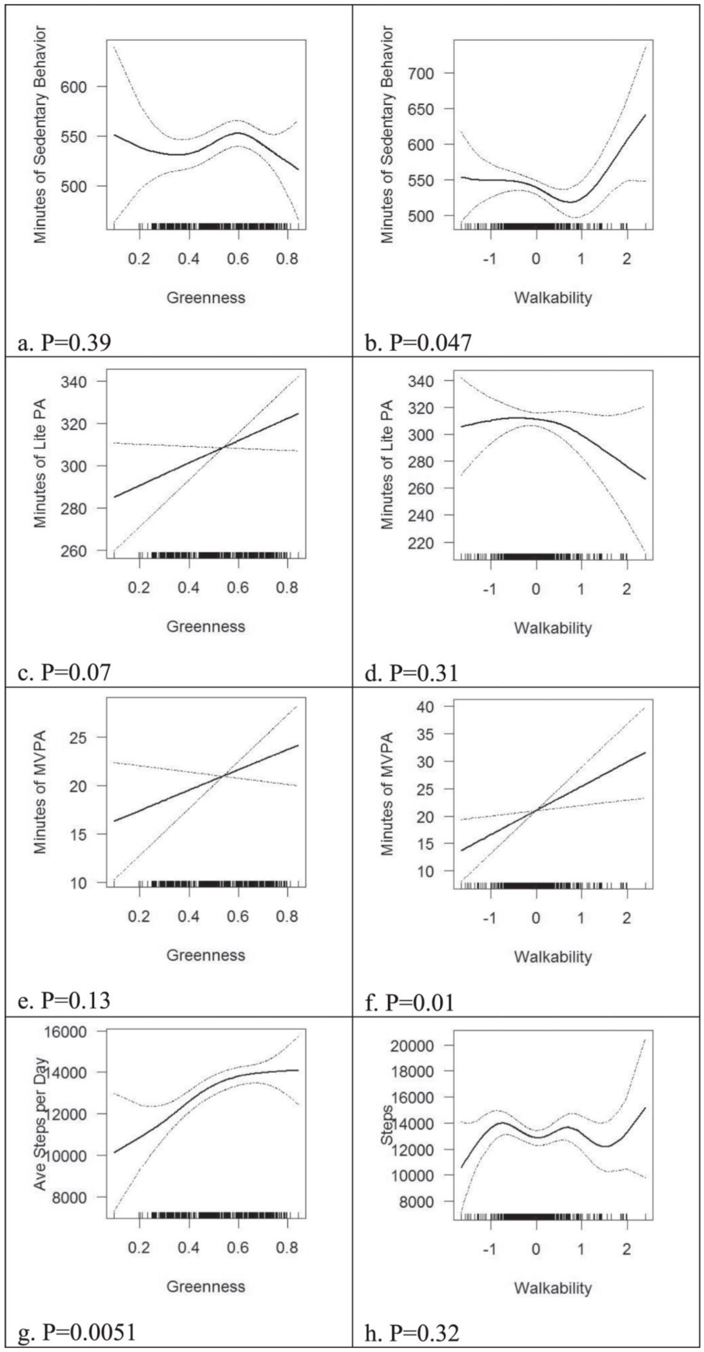

Fig. 2.

Fully-adjusted spline models for 200 m daily path area greenness and walkability and different measures of physical activity (PA) (sedentary behavior, light PA, moderate-vigorous PA, avg steps per day).

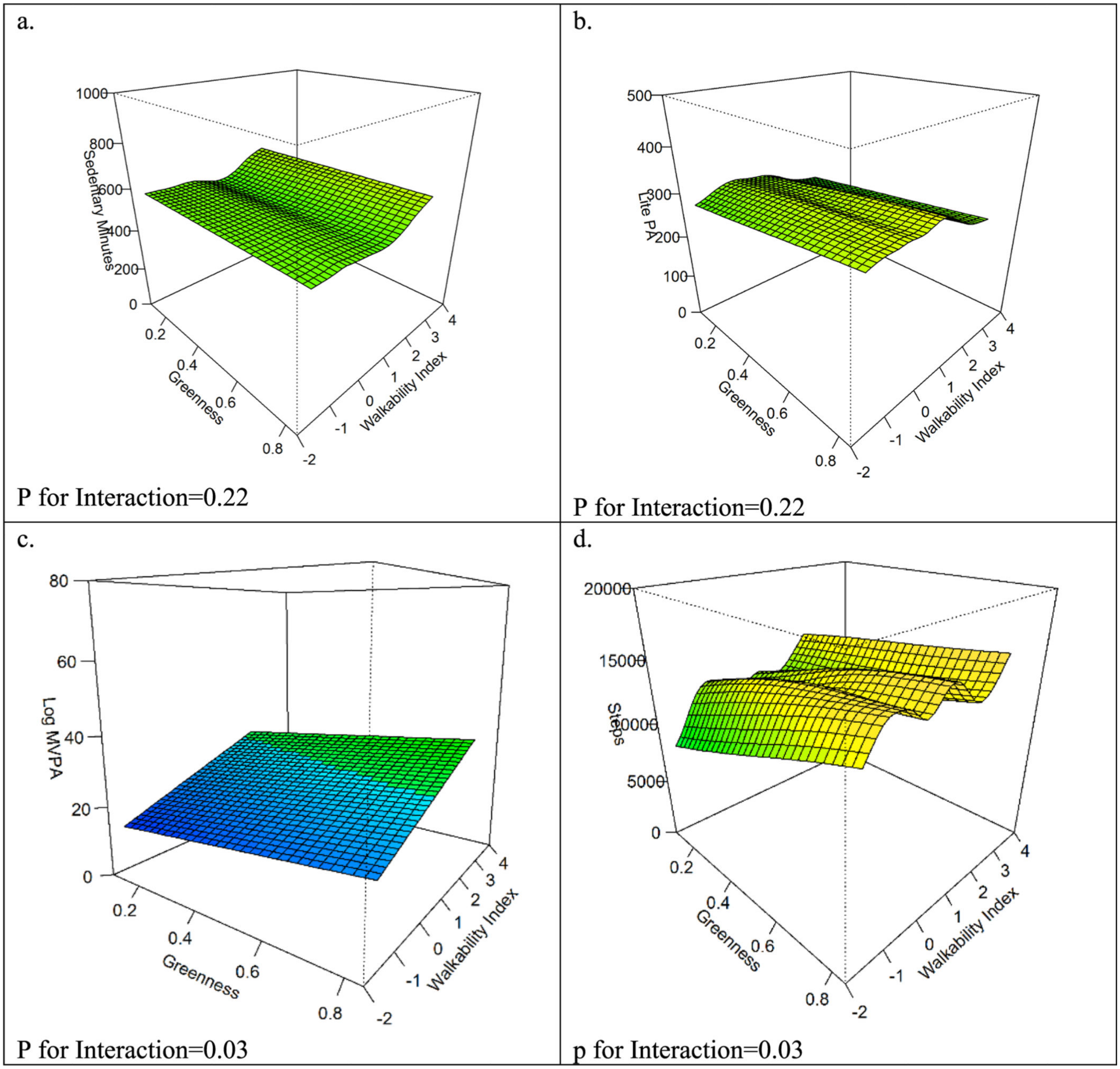

Fig. 3.

Interactions between greenness and walkability for a. Sedentary minutes; b. Light physical activity; c. Moderate-vigorous physical activity; d. Steps.

Table 1

Characteristics of study population of working adults from four sites (UCSD, WUSTL, Nurses' Health Study II cohort (Harvard), and breast cancer survivors (UPenn)) who provided seven day samples of GPS and accelerometer data (N = 354).

	N	%
Race		
White	279	78.8
Black	58	16.4
Other	17	4.8
Marital status		
Never married, divorced/separated, widowed	103	29.1
Presently married or partnered cohabitation	251	70.9
Educational attainment		
Less than college	111	31.4
College	119	33.6
Graduate degree	124	35.0
Household income		
Less than $50 k	79	22.3
$50 k–$69 k	54	15.3
Over $70 k	163	46.1
Don't know or refused	58	16.4
Employment status		
Missing or refused	4	1.1
Full time	180	50.9
Part time	79	22.3
Homemaker, unemployed, unable to work	32	9.0
Retired	59	16.7
Commute mode		
All other modes	322	91.0
Walk or bike to work	32	9.0
Health status		
Poor, fair, good	163	46.1
Very good, excellent	191	54.0
Study site		
Harvard	91	25.7
Penn	116	32.8
UCSD	69	19.5
WUSTL	78	22.0