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GPS-based exposure to greenness and walkability and accelerometry-based physical activity

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Abstract

Background—Physical inactivity is a risk factor for cancer that may be influenced by environmental factors. Indeed, dense and well-connected built environments and environments with natural vegetation may create opportunities for higher routine physical activity. However, studies have focused primarily on residential environments to define exposure and self-reported methods to estimate physical activity. The current study explores the momentary association between minute-level global positioning systems (GPS)-based greenness exposure and time-matched objectively measured physical activity.

Methods—Adult women were recruited from sites across the US. Participants wore a GPS device and accelerometer on the hip for 7 days to assess location and physical activity at minute-level epochs. GPS records were linked to 250m resolution satellite-based vegetation data and Census Block Group-level EPA Smart Location Database walkability data. Minute-level generalized

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additive mixed models were conducted to test for associations between GPS measures and accelerometer count data, accounting for repeated measures within participant and allowing for deviations from linearity using splines.

Results—Among 360 adult women (mean age of 55.3 ± 10.2 years), we observed positive nonlinear relationships between physical activity and both greenness and walkability. In exploratory analyses, the relationship between environmental factors and physical activity were strongest among those who were White, had higher incomes, and who were middle-aged.

Conclusions—Our results indicate that higher levels of physical activity occurred in areas with higher greenness and higher walkability.

Impact—Findings suggest that planning and design policies should focus on these environments to optimize opportunities for physical activity.

Keywords

Greenness; Walkability; Physical Activity; Accelerometry; Global Positioning Systems

Introduction

Physical inactivity is a major behavioral risk factor for cancer. Substantial evidence links increased physical activity with reduced risk of cancers of the colon and breast and may reduce the risk of endometrial cancer (1–7). Recent analyses have demonstrated that inadequate physical activity in the US contributes to over 12% of breast and colon cancers. In terms of preventable causes of disease, this is on par with the disease burden of smoking (8). However, in 2015 less than 50% of Americans met the guideline of 150 minutes of moderate-intensity aerobic activity per week, and older women were the least likely to meet guidelines (9).

Increasingly, research has demonstrated that physical activity patterns may be influenced by environmental factors (10, 11). The social-ecological model posits that the dynamic social, physical, and ecological contexts to which people are exposed play a role in driving individual behaviors, including physical activity (12). For instance, studies have illustrated that features of the built environment, such as the concentration of destinations and well-connected streets that increase the efficiency in reaching those destinations, may create opportunities for higher levels of routine physical activity (10). This substantial but growing body of literature (13) has demonstrated consistent associations between the built environment and physical activity from predominantly observational studies with self-reported outcome data (14). In addition, access to green, natural environments has also been associated with increased physical activity, likely because these settings reduce exposure to noise, pollution, and extreme temperatures, and provide opportunities for exercise, social interactions, and psychological restoration (11). This research is bolstered by the theory of biophilia, which posits that humans have evolved with nature to have an affinity for nature (15), as well as the psychoevolutionary theory (16), which suggests that being surrounded by nature may have a direct restorative effect on cognition and may decrease stress. Studies investigation the association between greenness and physical activity are primarily cross-sectional, and rarely measure objective physical activity (11). Better measures and

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evaluation of the built and natural environment related to physical activity enable improved and evidence-based interventions. Interventions may include a variety of social or ecological modifications, including changes in economic investment and land-use or transportation policy (10–12, 17–20).

However, the majority of studies examining built and natural environments in the context of physical activity have used static measures of exposure, as well as self-reported measures for physical activity. Many studies of environmental drivers of behavior have focused on the area around the residential address to define environmental exposures, despite the fact that individuals typically spend more than 50% of their time away from home (21). Indeed, a systematic review of studies on the built environment and physical activity suggested that more studies should explore context-specific physical activity (22). Studies also commonly rely on participants' accurate recall and self-reporting of physical activity behavior through questionnaires rather than objective means (23). Global positioning systems (GPS) enable the collection of time-indexed geographic coordinates, which can be used to represent the various locations an individual visits throughout the day (24). Accelerometry provides precise estimates of movement, which can be used to estimate physical activity. Combining GPS and accelerometry data with geographic information systems (GIS) layers supplies objective and unobtrusive measures with high accuracy. These measures empower analyses of 'spatial energetics' to examine how environmental characteristics, space, and time are linked to physical activity with high spatio-temporal resolution, providing insights into the environments in which physical activity takes place (25).

Our objective was to assess the association between minute-level GPS linked with high-resolution information on walkability and greenness exposure and time-matched objectively measured physical activity using data from a multi-site study of women across the United States. We also aimed to determine if these associations were linear (26), to examine interactions between walkability and greenness, and to assess effect modification by measures of age, race, and socioeconomic status.

Materials and Methods

Study Protocol

A convenience sample of female participants was recruited from four sites (Harvard TH Chan School of Public Health (Harvard), University of California, San Diego (UCSD), University of Pennsylvania (UPenn), and Washington University in St. Louis (WUSTL)) involved in the NCI-funded Transdisciplinary Research in Energetics and Cancer (TREC) initiative (27). The sample included working adults (UCSD and WUSTL), members of a prospective cohort of nurses (Harvard), and breast cancer survivors (UPenn).

Participants completed baseline surveys and were asked to wear objective measurement devices over seven consecutive days and nights. Participants were instructed to wear both an Actigraph GT3X+ accelerometer and a Qstarz BT1000X GPS device on the hip during all waking hours, except when showering, bathing, or swimming. Participants removed the devices at night to charge the GPS device. Participants were enrolled in the study across the four sites over the course of 12-months in 2012–2013.

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All participants completed a standardized study protocol, and all sites were trained extensively on data collection, participant compliance, and data screening techniques. Study protocols specific to the collection of GPS and accelerometer data were identical across all sites and all data used in these analyses were centrally pooled and uniformly processed at UCSD. Participant data were excluded if there were fewer than five days of data with 600 minutes of wear time or fewer than four days with 3000 minutes of total accelerometer wear time.

Eligibility criteria were: female, 21 to 75 years old, self-reported BMI between 21.0 and 39.9, ability to ambulate unassisted, not pregnant or breast-feeding, and willing to wear monitoring devices for seven days. The institutional review boards at each university site approved the study protocol and consent forms, and all participants provided written informed consent.

Accelerometer Data

Accelerometer data were screened manually for wear time compliance. We collected raw accelerometer data at 30 Hertz from the hip accelerometer and aggregated as counts to 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 (28). Data were manually screened by trained personnel to identify valid days for analysis. Validity criteria included daily total wearing time, counts of wearing periods, typical daily wear patterns, and accelerometer malfunction. Fewer than 600 minutes of wear or fewer than four wear periods indicated the device was not worn consistently enough to represent a normal day. Counts per minute (CPM) from the vertical axis of the hip accelerometer were used as our primary measure of total physical activity intensity. Analyses of CPM were chosen to remain agnostic to specific cutpoints for activity, as recent analyses have shown that total CPM holds stronger correlations with gold standard doubly-labeled water measures of physical activity energy expenditure compared to moderate- to vigorous-intensity measures of physical activity based on cutpoints (analysis under review).

GPS Data

The Qstarz GPS device logged location coordinates, distance, speed, elevation, and time. The Qstarz has reported accuracy of 3 m, and validation studies demonstrate median error differing slightly by behavior (from 3.9 m for walking to 0.5m for driving) and environment (from 5.2 m in urban canyons to 0.7 m in open areas) (29). All GPS devices were evaluated for this level of accuracy before being deployed. Devices were configured to record location and time data at 15 second intervals.

Merging GPS and Accelerometry Data

GPS data were processed and joined to the accelerometer data using the Personal Activity and Location Measurement System (PALMS) (30, 31). Data were aggregated and merged at the minute level. After consideration of accelerometer non-wear time and missing GPS data, valid wear days were defined as days with a minimum of 600 minutes with combined accelerometer and GPS data.

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GIS Data

Greenness—Normalized Difference Vegetation Index (NDVI) values were used to estimate the amount green vegetation over the GPS data. Reflected sunlight from satellite-measured red and near-infrared bands are converted to generate NDVI values with a range of −1.0 to 1.0, with larger values indicating higher levels of vegetation density (33). NDVI values from 250 × 250 m satellite data were obtained for each GPS coordinate as a measure of momentary exposure. For this study, we used data from the Moderate-resolution Imaging Spectroradiometer (MODIS) deployed on NASA's Terra satellite. Imagery from July 2012 was obtained to approximate the greenness levels at the time of data collection (34). Supplemental Figure 1a shows a participant's GPS data linked to the NDVI layer.

Walkability—Minute-level GPS coordinate data were linked to a GIS layer of a walkability index based on US Environmental Protection Agency (EPA) Smart Location Database, which includes data on nationwide Census Block Group-level population density, street connectivity, and land use mix. The Smart Location Database provides nationwide geographic data on 90 attributes summarizing characteristics such as housing density, diversity of land use, neighborhood design, destination accessibility, transit service, employment, and demographics at the Census Block Group level (35). A Census Block Group is the smallest geographic unit for which the US Census Bureau releases data. A walkability index was used to estimate momentary exposure data at the Census Block Group resolution. The following measures were used to create the walkability index: Gross population density (people/acre) on unprotected land; Street intersection density (weighted, with auto-oriented intersections eliminated); and Land Use Diversity based on the mix of retail, office, service, industrial, entertainment, education, healthcare, and public administration employment in the Census Block Group. We then created Z-scores (mean of 0, standard deviation of 1) for each of these measures across all Block Groups in the US and summed these Z-scores to estimate a walkability index for each Census Block Group. A higher walkability index indicates a more walkable neighborhood. Each GPS point was linked to a Block Group to create a minute-level exposure to walkability. Supplemental Figure 1b shows a participant's GPS data linked to the walkability layer.

Demographics

Demographic data were collected from all participants through a baseline survey. Information gathered included age (years), race (White; Black; Other), educational attainment (Less than College; College; Graduate Degree), employment status (Full Time; Part Time; Homemaker, Unemployed, or Unable to Work; Retired; Missing or Not Provided), and household annual income from all sources (<$50K per year; $50K–$69K per year; $70K+ per year; Missing or Refused to Answer).

Statistical Analysis

We created minute-level generalized additive mixed models to examine the relationship between walkability or greenness and physical activity, accounting for temporal clustering of repeated measures within each participant. Models were adjusted for study site, age, race, educational attainment, employment status, and household annual income. We also

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considered models including both greenness and walkability to adjust for potential confounding between environmental features. Natural splines were used to test for deviations from linearity. We compared Akaike's Information Criteria (AIC) values for linear versus nonlinear models. Nonlinear models had lower AIC values, suggesting a better model fit. Sensitivity analyses were conducted excluding accelerometry count data that was greater than three times the standard deviation of accelerometer counts to explore the influence of outliers. 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. Exploratory analyses also examined whether the relationship between environmental factors and physical activity differed according to age, race, education, income, employment status, season of sampling period (Fall, Winter, Spring, Summer), or weekday/weekend sampling day.

Results

A total of 360 participants provided data for this analysis, with an average of 6.3 days of data per participant. The mean age of participants was 55.3 (SD 10.2) years (Table 1). Approximately 78% of participants were White, while about a third of the sample had a college education and half were employed full-time. Approximately half (46%) of participants reported having a household income over $70,000 per year.

We observed generally positive nonlinear relationships between momentary physical activity and both greenness and walkability, after accounting for age, race, education, income, and employment status (Figure 1). These analyses were also adjusted for greenness or walkability, as appropriate. Increasing greenness was associated with higher physical activity, with the highest levels of activity occurring at greenness >0.60. We observed a nonlinear J-shaped relationship between exposure to walkability and physical activity, where physical activity was lowest in areas with a walkability index of zero and increased greatly in areas with a walkability index >0. Sensitivity analyses excluding outlier data are shown in Supplemental Figure 2. The relationship between greenness and physical activity was greatly attenuated, while the relationship between walkability and physical activity persisted.

Analyses examining interactions showed that the relationship between greenness and physical activity differed by levels of neighborhood walkability, and vice versa (surface spline shown in Figure 2). Specifically, at low levels of walkability, the relationship between greenness and physical activity was positive (blue to green portion of surface spline). At higher levels of walkability, however, the relationship between greenness and physical activity plateaued slightly (yellow portion of spline). Conversely, the generally positive J-shaped relationship between walkability and physical activity persisted across all levels of greenness. The highest levels of activity overall were observed in areas with the highest levels of neighborhood walkability.

Figure 3 shows surface splines examining the relationship between environmental factors and physical activity by age. In general, we observed that higher levels of physical activity occurred in areas of higher greenness and walkability across all ages. Levels of physical activity were consistently lowest among the oldest participants. Supplemental Figures 3–8

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show the relationship between greenness and physical activity stratified by race, education, employment, income, sampling season, and weekday / weekend, respectively. Although this sample included primarily White participants, the shape of the curves differed slightly among White participants compared to Black participants and there was little observed relationship between greenness and physical activity among participants of other races (Supplemental Figure 3). The relationship between greenness and physical activity was strongest among participants with higher incomes (Supplemental Figure 6). The association between greenness and physical activity was weakest when sampling was conducted during the winter (Supplemental Figure 7), and relationships were generally stronger on weekends compared to weekdays (Supplemental Figure 8). Relationships were generally consistent across levels of education and employment status. Associations between walkability and physical activity are shown in Supplemental Figures 9–14. Again, although there were few non-White participants in this study, the relationship between walkability and physical activity was not apparent among Black participants (Supplemental Figure 9). The relationship between walkability and physical activity was not evident among participants making $50,000–69,000, who made up 15% of the sample (Supplemental Figure 12). Relationships between walkability and physical activity were fairly consistent across seasons (Supplemental Figure 13). The association between walkability and physical activity was stronger on weekdays compared to weekends (Supplemental Figure 14). Associations were generally consistent across levels of education and employment status.

Discussion

In this analysis of GPS-based environmental factors and physical activity, objectively measured by accelerometry, we observed consistently positive nonlinear relationships, with the highest levels of physical activity occurring in areas with the highest levels of greenness and neighborhood walkability among a sample of adult women from regions across the United States. When examining both greenness and walkability together, we observed that at low levels of walkability, the relationship between greenness and physical activity was positive, whereas at higher levels of walkability, there were weaker relationships between greenness and physical activity. There was a strong nonlinear positive relationship between walkability and physical activity that persisted across all levels of greenness. The highest levels of activity overall were observed in areas with the highest levels of neighborhood walkability, indicating that participants in this study were most active in walkable urban environments regardless of how green these environments were. In analyses excluding outliers for physical activity, the relationship between greenness and physical activity diminished, which suggests that the most extreme levels of physical activity occurred in the greenest settings. Conversely, excluding outliers had little effect on the relationship between walkability and physical activity. This indicates that the relationship between walkability and physical activity may be driven primarily by routine levels of physical activity, such as walking.

There was some evidence that the relationship between environmental factors and activity differed by a participant’s race and income, although there was little variation by these factors among the participants in this study. Although we had few Black participants, our finding of a potentially negative association between walkability and physical activity

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among Black women is consistent with two literature reviews, which found widely varying associations between the built environment and physical activity among Black participants (36, 37). These studies suggest that physical activity preferences might differ between White and Black individuals, and therefore environments that support physical activity may not be conducive to Black participants. Additionally, unmeasured factors such as perceived safety, crime, and environmental quality could account for the lack of association. While these exposures are not considered here, future analyses may consider how these factors might moderate the relationship between physical activity and neighborhood walkability. We also observed some variation in relationships by season, where the association between greenness and physical activity was not present during the winter. Finally, greenness was more strongly linked to physical activity on weekends, while walkability held stronger relationships with physical activity on weekdays.

These findings suggest that, consistent with theory on the built environment, individuals may obtain higher levels of physical activity in more walkable environments. Although relationships were not as strong, this analysis also suggests that higher levels of physical activity also occurred in greener areas. The J-shaped relationship between neighborhood walkability and physical activity is consistent with the theory that when the built environment reaches a certain threshold for density and connectivity with sufficient land-use mix, it becomes more convenient to walk or take transit than to drive (38). Simultaneously, our results suggest that although higher levels of greenness were associated with higher levels of physical activity generally, levels of physical activity increased most rapidly as greenness increased to the highest levels (greenness>0.6). This suggests that physical activity was most likely to take place in dense green spaces, including parks or forests. Analyses stratified by season suggest that participants were less likely to conduct physical activity in green areas during winter months, while season had less influence on activity in walkable areas. Additionally, activity in greener areas was less likely to occur during weekdays, while activity in walkable areas was less likely to take place during weekends. These findings by season and weekday / weekend are consistent with the idea that individuals are physically active in walkable environments during routine daily life (e.g., commuting), while they are more likely to obtain physical activity in greener environments during devoted time for recreation.

This study adds to the growing literature utilizing GPS, GIS, and accelerometry to elucidate relationships between the environment and physical activity. Although studies use varying methodologies, in general, evidence is mounting that both the built environment and greenness are linked to objectively-measured physical activity. McCrorie et al. (2014) conducted a small literature review on the nascent field of studies examining GPS and accelerometry (39). Although this review was limited to studies involving children, the authors reported consistent associations between higher moderate-vigorous physical activity in parks, greener areas, and areas with higher population density. In line with the present analysis, Almanza et al. (2012) studied 208 children in California who wore GPS devices and accelerometers (40). Using a methodology similar to the one described in our study, these researchers measured NDVI levels at 30-second epochs and found a 34% increased odds of momentary moderate-vigorous physical activity (95% CI 1.30, 1.38) for a 0.11 increase in NDVI. As part of the Residential Environment and Coronary Heart Disease

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(RECORD) GPS Study, Chaix et al. gathered seven days of GPS and accelerometry data on 227 participants in Paris (41). Analyses demonstrated that the probability of walking during a trip was 16% higher (95% CI 2%, 28%) when the trip originated in the top quartile of green space density and 20% higher (95% CI 7%, 33%) when the trip ended in the top quartile of green space density versus the bottom quartile. In addition, the probability of walking during a trip was 37% higher (95% CI 12%, 61%) when trip origin was in the top quartile of service density (public services, shops, entertainment facilities, etc.) and 47% higher (95% CI 23%, 68%) when the trip destination was in the top quartile of service density versus the bottom quartile. Duncan et al. (2016) analyzed GPS and accelerometry data from the same set of 227 RECORD participants in Paris. The authors found that trips that began in or concluded in neighborhoods with a high Walk Score, a composite measure of neighborhood walkability, were more likely to involve walking and involved a larger number of steps taken (42). Finally, Hirsch et al. (2016) measured the built environment within polygons around GPS points (activity spaces) gathered from 77 older adults in Vancouver, Canada, but observed that metrics of the built environment within these activity spaces were not associated with accelerometry-measured physical activity (43). The authors did, however, find that when they restricted analyses to GPS points during walking or bicycling, higher destination densities within these activity spaces were associated with higher activity levels. In total, the present analysis is consistent with the small body of literature finding positive associations between GPS-based exposure to greenness and walkability and accelerometer-measured physical activity. As far as the authors are aware, this is the first study to observe interactions between greenness and walkability, two environmental factors that have been suggested to influence physical activity.

While the present analysis contributes new insights on how environment is related to behavior, this study has a number of limitations. Our measure of physical activity was minute level total counts from vertical axis of hip-worn accelerometry data and we did not estimate time spent in specific intensities of physical activity. There is still a lack of consensus over how to best measure physical activity (44), and methodological advances, such as machine-learning approaches, promise to provide better classification of important physical activity behaviors in the future (45, 46). In addition, while GPS data provides higher temporal resolution for understanding an individual’s location in space, we know that GPS accuracy (29), missingness (32), and scatter (30) are consistent concerns. That said, methodologies to impute missing or scattered GPS data may improve data quality (47, 48). One potential problem that was not addressed is spatial autocorrelation; proximal GPS locations are likely to have similar walkability and greenness values and should not necessarily be considered independent observations. Moreover, even if GPS data were to be completely accurate, these data require joining with GIS layers to provide momentary estimates of environmental exposures. Numerous studies have documented inaccuracies in GIS layers’ representation of built environment variables (49–51), while a study has shown that satellite vegetation data correlates highly when compared to environmental psychologists’ evaluations of green spaces (52). Nevertheless, our satellite-based measure of greenness does not measure the quality of greenness (e.g., whether vegetation occurs in a vacant lot or a manicured park), does not provide information on vegetation structure, and does not detail vegetation species type. Therefore, our measure of greenness may represent only one dimension of exposure to nature that might influence physical activity. The representativeness of this sample is also limited. Participants who provided data were older adult women, and were relatively homogenous with respect to race and income. Finally, we are unable to establish from this analysis that environmental factors are the cause physical activity. In the context of spatial energetics research in observational studies, confounding by intrapersonal characteristics can occur through “selective daily mobility bias,” which arises when individual preferences simultaneously lead individuals to visit certain locations and also can drive the behaviors conducted in those locations (53, 54). Because of this bias, conclusions on how contextual measures “cause” physical activity behaviors within momentary analyses may be limited; however, our analysis does provide valuable evidence about the characteristics of environments where participants do obtain physical activity. This type of evidence may support the identification of environments that provide opportunities for individuals to be physically active.

The study did have a number of significant strengths, including a relatively large sample size for a study involving GPS and accelerometry. Although not intended to be representative of nationwide trends in environmental exposures and physical activity, the study involved a convenience sample of participants from multiple regions of the United States, which adds to the broader variability in environmental exposures. The use of nationwide datasets on greenness and walkability coupled with uniform study protocols across study sites allowed for the pooling of consistently collected data. The nonlinear mixed modeling approach to data analysis also provided novel insights into potential thresholds and complex relationships between environmental factors, while accounting for repeated measures. The collection of data on important demographic factors, including age and income, afforded exploratory stratified analyses. The examination of interactions between two GPS-based measures of greenness and walkability provides new insights into the relative strength of association of each environmental measure with physical activity. These analyses showed intriguing potential effect modification, which warrants further investigation in other samples.

While further studies are required to better understand how specific environmental factors drive healthy behaviors across diverse populations, this study contributes evidence that higher levels of physical activity takes place in dense and connected built environments and in areas with high levels of vegetation, regardless of whether this activity occurs near the home or not. Our findings also suggest that the built environment may be a more important factor than the natural environment when considering routine location-based physical activity. As the popularity of GPS- and accelerometer-enabled smartphones grows alongside accelerometry-based consumer wearable devices (55–58), these novel streams of spatial energetics data will provide translational insights into potential interventions to improve urban planning and green space development to optimize opportunities for physical activity and reduce cancer risk.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

1. Slattery ML. Physical activity and colorectal cancer. Sports Med. 2004; 34:239–52. [PubMed: 15049716]
2. IARC Handbooks of Cancer Prevention. Weight Control and Physical Activity. 2002
3. Ballard-Barbash, R., Friedenreich, C., Slattery, M., Thune, L. Obesity and body composition. In: Schottenfeld, D., Fraumeni, J., editors. Cancer Epidemiology and Prevention. 3. New York: Oxford University Press; 2006.
4. Lee IM. Physical activity and cancer prevention–data from epidemiologic studies. Med Sci Sports Exerc. 2003; 35:1823–7. [PubMed: 14600545]
5. Lynch BM, Neilson HK, Friedenreich CM. Physical activity and breast cancer prevention. Recent Results Cancer Res. 2011; 186:13–42. [PubMed: 21113759]
6. Kyu HH, Bachman VF, Alexander LT, Mumford JE, Afshin A, Estep K, et al. Physical activity and risk of breast cancer, colon cancer, diabetes, ischemic heart disease, and ischemic stroke events: systematic review and dose-response meta-analysis for the Global Burden of Disease Study 2013. Bmj. 2016; 354:i3857. [PubMed: 27510511]
7. Voskuil DW, Monninkhof EM, Elias SG, Vlems FA, van Leeuwen FE, Task Force Physical A. et al. Physical activity and endometrial cancer risk, a systematic review of current evidence. Cancer Epidemiol Biomarkers Prev. 2007; 16:639–48. [PubMed: 17416752]
8. Lee IM, Shiroma EJ, Lobelo F, Puska P, Blair SN, Katzmarzyk PT. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet. 2012; 380:219–29. [PubMed: 22818936]
9. Ward, B., Clarke, T., Nugent, C., Schiller, J. Early release of selected estimates based on data from the 2015 National Health Interview Survey. National Center for Health Statistics. , editor. 2016.
10. Sallis JF, Floyd MF, Rodriguez DA, Saelens BE. Role of built environments in physical activity, obesity, and cardiovascular disease. Circulation. 2012; 125:729–37. [PubMed: 22311885]
11. James P, Banay RF, Hart JE, Laden F. A Review of the Health Benefits of Greenness. Curr Epidemiol Rep. 2015; 2:131–42. [PubMed: 26185745]
12. Krieger N. Embodiment: a conceptual glossary for epidemiology. J Epidemiol Community Health. 2005; 59:350–5. [PubMed: 15831681]
13. Harris JK, Lecy J, Hipp JA, Brownson RC, Parra DC. Mapping the development of research on physical activity and the built environment. Prev Med. 2013; 57:533–40. [PubMed: 23859932]
14. Ferdinand AO, Sen B, Rahurkar S, Engler S, Menachemi N. The Relationship Between Built Environments and Physical Activity: A Systematic Review. Am J Public Health. 2012; 102:e7–e13.
15. Wilson, EO. Biophilia. Cambridge: Harvard University Press; 1984.
16. Ulrich RS. View through a window may influence recovery from surgery. Science. 1984; 224:420–1. [PubMed: 6143402]
17. Durand CP, Andalib M, Dunton GF, Wolch J, Pentz MA. A systematic review of built environment factors related to physical activity and obesity risk: implications for smart growth urban planning. Obes Rev. 2011; 12:e173–82. [PubMed: 21348918]
18. Pasanen TP, Tyrvainen L, Korpela KM. The Relationship between Perceived Health and Physical Activity Indoors, Outdoors in Built Environments, and Outdoors in Nature. Appl Psychol Health Well Being. 2014

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19. Lee AC, Maheswaran R. The health benefits of urban green spaces: a review of the evidence. J Public Health (Oxf). 2011; 33:212–22. [PubMed: 20833671]
20. Sugiyama T, Leslie E, Giles-Corti B, Owen N. Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships? J Epidemiol Community Health. 2008; 62:e9. [PubMed: 18431834]
21. Hurvitz PM, Moudon AV. Home versus nonhome neighborhood: quantifying differences in exposure to the built environment. Am J Prev Med. 2012; 42:411–7. [PubMed: 22424255]
22. Ding D, Gebel K. Built environment, physical activity, and obesity: what have we learned from reviewing the literature? Health Place. 2012; 18:100–5. [PubMed: 21983062]
23. Lee IM, Shiroma EJ. Using accelerometers to measure physical activity in large-scale epidemiological studies: issues and challenges. Br J Sports Med. 2014; 48:197–201. [PubMed: 24297837]
24. Jankowska MM, Schipperijn J, Kerr J. A Framework for Using GPS Data in Physical Activity and Sedentary Behavior Studies. Exercise and sport sciences reviews. 2015; 43:48–56. [PubMed: 25390297]
25. James P, Jankowska M, Marx C, Hart JE, Berrigan D, Kerr J, et al. "Spatial Energetics": Integrating Data From GPS, Accelerometry, and GIS to Address Obesity and Inactivity. Am J Prev Med. 2016; 51:792–800. [PubMed: 27528538]
26. Sallis JF, Cerin E, Conway TL, Adams MA, Frank LD, Pratt M, et al. Physical activity in relation to urban environments in 14 cities worldwide: a cross-sectional study. Lancet. 2016; 387:2207–17. [PubMed: 27045735]
27. Patterson RE, Colditz GA, Hu FB, Schmitz KH, Ahima RS, Brownson RC, et al. The 2011–2016 Transdisciplinary Research on Energetics and Cancer (TREC) initiative: rationale and design. Cancer Causes Control. 2013; 24:695–704. [PubMed: 23378138]
28. Choi L, Liu Z, Matthews CE, Buchowski MS. Validation of accelerometer wear and nonwear time classification algorithm. Med Sci Sports Exerc. 2011; 43:357–64. [PubMed: 20581716]
29. Schipperijn J, Kerr J, Duncan S, Madsen T, Klinker CD, Troelsen J. Dynamic Accuracy of GPS Receivers for Use in Health Research: A Novel Method to Assess GPS Accuracy in Real-World Settings. Front Public Health. 2014; 2:21. [PubMed: 24653984]
30. Carlson JA, Jankowska MM, Meseck K, Godbole S, Natarajan L, Raab F, et al. Validity of PALMS GPS Scoring of Active and Passive Travel Compared to SenseCam. Med Sci Sports Exerc. 2014
31. Demchak, B., Kerr, J., Raab, F., Patrick, K., Kruger, IH. Hawaii International Conference on System Science (HICSS). IEEE; 2012. PALMS: a modern coevolution of community and computing using policy driven development; p. 2735-44.
32. Meseck K, Jankowska MM, Schipperijn J, Natarajan L, Godbole S, Carlson JA, et al. Is missing geographic position system (GPS) data in accelerometry studies a problem, and is imputation the solution? Geospat Health. 2016; 11
33. Kriegler, F., Malila, W., Nalepka, R., Richardson, W. Preprocessing transformations and their effects on multispectral recognition. Proceedings of the Sixth International Symposium on Remote Sensing of Environment; 1969; Ann Arbor, MI. p. 97-131.
34. Carroll, ML.DiMiceli, CM.Sohlber, RA., Townshend, JRG., editors. 250m MODIS Normalized Difference Vegetation Index. College Park, MD: 2004.
35. US Environmental Protection Agency. Smart Location Database. 2014. [cited 2016 October 24]; Available from: https://www.epa.gov/smartgrowth/smart-location-mapping#SLD
36. Lovasi GS, Hutson MA, Guerra M, Neckerman KM. Built environments and obesity in disadvantaged populations. Epidemiologic reviews. 2009; 31:7–20. [PubMed: 19589839]
37. Casagrande SS, Whitt-Glover MC, Lancaster KJ, Odoms-Young AM, Gary TL. Built environment and health behaviors among African Americans: a systematic review. Am J Prev Med. 2009; 36:174–81. [PubMed: 19135908]
38. Forsyth AJ, Oakes JM, Schmitz KH, Hearst M. Does residential density increase walking and other physical activity? Urban Studies. 2007; 44:679–97.
39. McCrorie PR, Fenton C, Ellaway A. Combining GPS, GIS, and accelerometry to explore the physical activity and environment relationship in children and young people – a review. Int J Behav Nutr Phys Act. 2014; 11:93. [PubMed: 25356782]

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40. Almanza E, Jerrett M, Dunton G, Seto E, Pentz MA. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. Health Place. 2012; 18:46–54. [PubMed: 22243906]

41. Chaix B, Kestens Y, Duncan DT, Brondeel R, Meline J, El Aarbaoui T, et al. A GPS-Based Methodology to Analyze Environment-Health Associations at the Trip Level: Case-Crossover Analyses of Built Environments and Walking. Am J Epidemiol. 2016; 184:570–8. [PubMed: 27659779]

42. Duncan DT, Meline J, Kestens Y, Day K, Elbel B, Trasande L, et al. Walk Score, Transportation Mode Choice, and Walking Among French Adults: A GPS, Accelerometer, and Mobility Survey Study. Int J Environ Res Public Health. 2016; 13

43. Hirsch JA, Winters M, Ashe MC, Clarke P, McKay H. Destinations That Older Adults Experience Within Their GPS Activity Spaces Relation to Objectively Measured Physical Activity. Environ Behav. 2016; 48:55–77. [PubMed: 26783370]

44. Kelly P, Fitzsimons C, Baker G. Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. Int J Behav Nutr Phys Act. 2016; 13:32. [PubMed: 26931142]

45. Ellis K, Godbole S, Marshall S, Lanckriet G, Staudenmayer J, Kerr J. Identifying Active Travel Behaviors in Challenging Environments Using GPS, Accelerometers, and Machine Learning Algorithms. Front Public Health. 2014; 2:36. [PubMed: 24795875]

46. Kerr J, Marinac C, Ellis K, Godbole S, Hipp J, Glanz K, et al. Comparison of accelerometry methods for estimating physical activity. Med Sci Sports Exerc. 2016 In Press.

47. Ogle J, Guensle R, Bachman W, Koutsak M, Wolf J. Accuracy of global positioning system for determining driver performance parameters. Trans Res Record. 2002; 1818:12–24.

48. Kerr J, Duncan S, Schipperijn J. Using global positioning systems in health research: a practical approach to data collection and processing. Am J Prev Med. 2011; 41:532–40. [PubMed: 22011426]

49. Liese AD, Barnes TL, Lamichhane AP, Hibbert JD, Colabianchi N, Lawson AB. Characterizing the food retail environment: impact of count, type, and geospatial error in 2 secondary data sources. Journal of nutrition education and behavior. 2013; 45:435–42. [PubMed: 23582231]

50. Liese AD, Colabianchi N, Lamichhane AP, Barnes TL, Hibbert JD, Porter DE, et al. Validation of 3 food outlet databases: completeness and geospatial accuracy in rural and urban food environments. Am J Epidemiol. 2010; 172:1324–33. [PubMed: 20961970]

51. Powell LM, Han E, Zenk SN, Khan T, Quinn CM, Gibbs KP, et al. Field validation of secondary commercial data sources on the retail food outlet environment in the U.S. Health Place. 2011; 17:1122–31. [PubMed: 21741875]

52. Rhew IC, Vander Stoep A, Kearney A, Smith NL, Dunbar MD. Validation of the normalized difference vegetation index as a measure of neighborhood greenness. Ann Epidemiol. 2011; 21:946–52. [PubMed: 21982129]

53. Chaix B, Kestens Y, Perchoux C, Karusisi N, Merlo J, Labadi K. An interactive mapping tool to assess individual mobility patterns in neighborhood studies. Am J Prev Med. 2012; 43:440–50. [PubMed: 22992364]

54. Chaix B, Meline J, Duncan S, Merrien C, Karusisi N, Perchoux C, et al. GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? Health Place. 2013; 21:46–51. [PubMed: 23425661]

55. International Data Corporation. Worldwide Wearable Computing Market Gains Momentum with Shipments Reaching 19.2 Million in 2014 and Climbing to Nearly 112 Million in 2018, Says IDC 2014. [cited 2014 July 31]; Available from: http://www.idc.com/getdoc.jsp?containerId=prUS24794914

56. Adam Noah J, Spierer DK, Gu J, Bronner S. Comparison of steps and energy expenditure assessment in adults of Fitbit Tracker and Ultra to the Actical and indirect calorimetry. J Med Eng Technol. 2013; 37:456–62. [PubMed: 24007317]

57. Lee JM, Kim Y, Welk GJ. Validity of Consumer-Based Physical Activity Monitors. Med Sci Sports Exerc. 2014

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58. Takacs J, Pollock CL, Guenther JR, Bahar M, Napier C, Hunt MA. Validation of the Fitbit One activity monitor device during treadmill walking. Journal of science and medicine in sport / Sports Medicine Australia. 2013

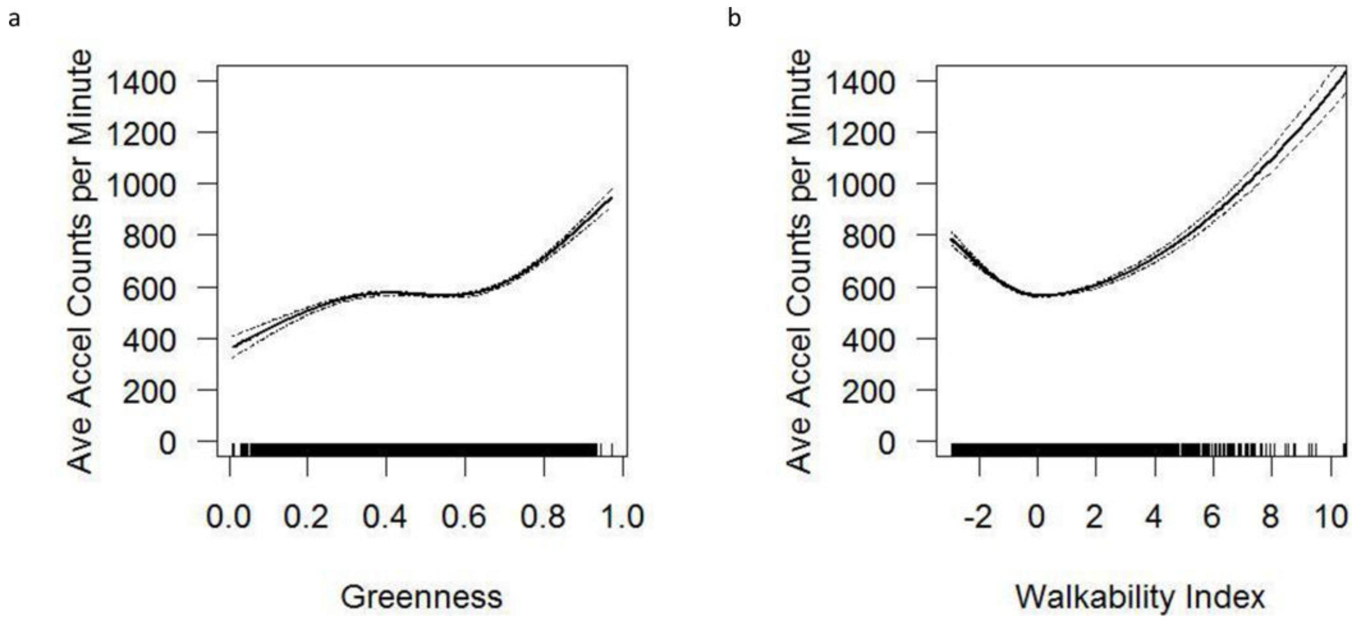

Figure 1. Nonlinear Relationship between Activity and a. Greenness and b. Neighborhood Walkability

Note: Analyses were adjusted for study site, age, race, education, income, and employment status, as well as greenness or walkability as appropriate. Greenness defined using MODIS Normalized Difference Vegetation Index; Walkability defined using EPA Smart Location Database information on gross population density, street intersection density, and land use diversity

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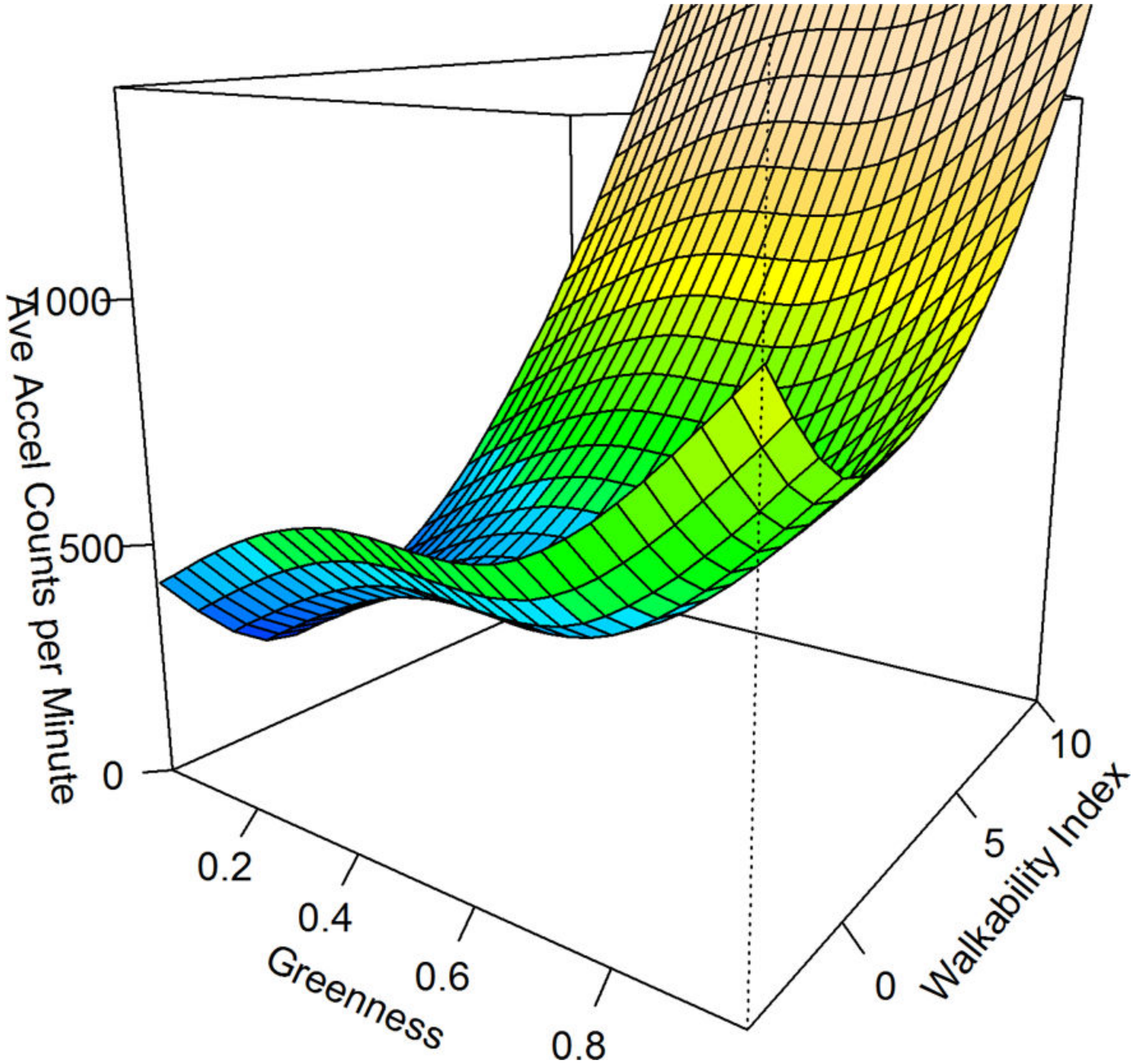

Figure 2. Surface Spline for Interaction between Greenness and Walkability

Note: Analysis was adjusted for study site, age, race, education, income, and employment status. Greenness defined using MODIS Normalized Difference Vegetation Index; Walkability defined using EPA Smart Location Database information on gross population density, street intersection density, and land use diversity

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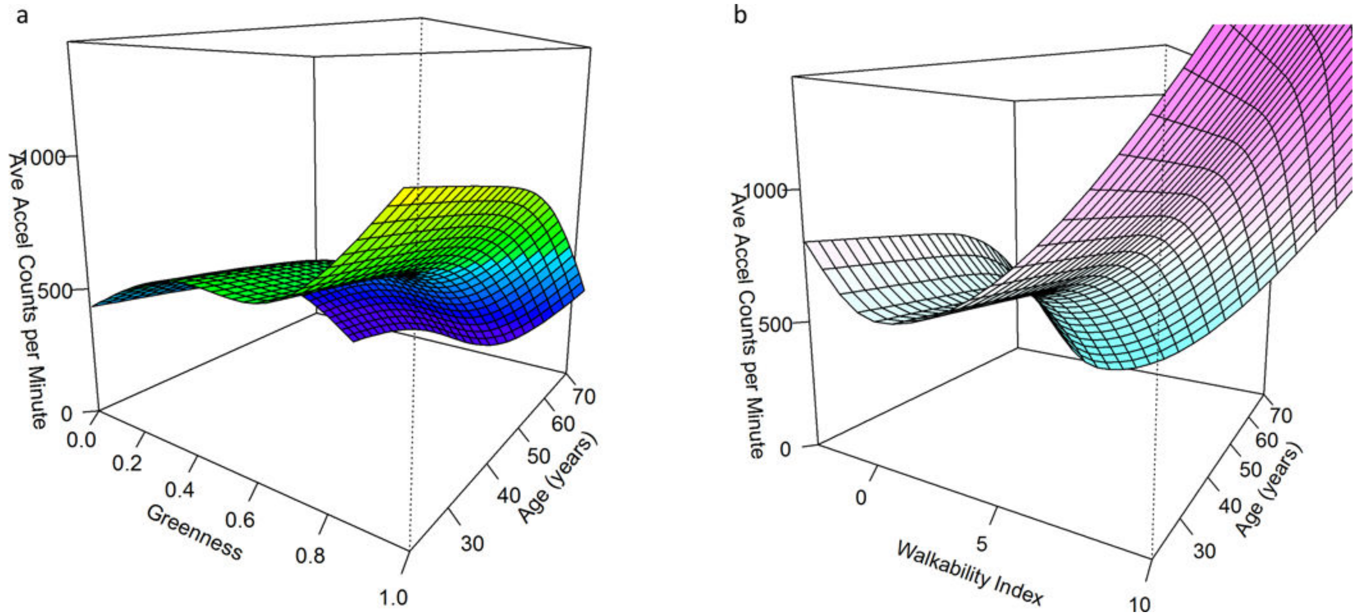

Figure 3. Surface Splines for Physical Activity by Age and a. Greenness and b. Walkability

Note: Analyses were adjusted for study site, race, education, income, and employment status. Greenness defined using MODIS Normalized Difference Vegetation Index; Walkability defined using EPA Smart Location Database information on gross population density, street intersection density, and land use diversity

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Table 1

Participant Characteristics (N=360)

	Mean	Range
Age (years)	55.3	22, 82
Momentary Exposure to Greenness	0.52	0.09, 0.83
Momentary Exposure to Walkability Index	0.23	−1.66, 6.30
Accelerometer Counts per Minute	562.1	43.0, 2290.9
Race	**N**	**%**
White	282	78.3%
Black	60	16.7%
Other	18	5.0%
Educational Attainment		
Less than College	115	31.9%
College	121	33.6%
Graduate Degree	124	34.4%
Employment Status		
Full Time	181	50.3%
Part Time	81	22.5%
Homemaker, Unemployed, Unable to Work	32	8.9%
Retired	61	16.9%
Missing or Refused to Answer	5	1.4%
Household Annual Income from All Sources		
<$50K	83	23.1%
$50–$69K	54	15.0%
$70K+	165	45.8%
Missing or Refused to Answer	58	16.1%
Study Site		
Harvard TH Chan School of Public Health (Nationwide Study)	91	25.3%
University of Pennsylvania (Philadelphia, PA)	119	33.1%
University of California, San Diego (San Diego, CA)	71	19.7%
Washington University in St. Louis (St. Louis, MO)	79	21.9%
Sampling Season		
Winter	107	29.7%
Spring	131	36.4%
Summer	33	9.2%
Fall	89	24.7%

Note: Greenness defined using MODIS Normalized Difference Vegetation Index; Walkability defined using EPA Smart Location Database information on gross population density, street intersection density, and land use diversity