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Minute level smartphone derived exposure to greenness and consumer wearable derived physical activity in a cohort of US women

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Abstract

Background: Inconsistent results have been found in the literature on associations of greenness, or vegetation quantity, and physical activity. However, few studies have assessed associations between mobility-based greenness and physical activity from mobile health data from smartphone and wearable devices with fine spatial and temporal resolution.

Methods: We assessed mobility-based greenness exposure and wearable accelerometer data from participants in the US-based prospective Nurses' Health Study 3 cohort Mobile Health (mHealth) Substudy (2018–2020). We recruited 500 female participants with instructions to wear devices over four 7-day sampling periods equally spaced throughout the year. After restriction criteria there were 337 participants (mean age 36 years) with n =639,364 unique observations. Normalized Difference Vegetation Index (NDVI) data were derived from 30 m x 30 m Landsat-8 imagery and spatially joined to GPS points recorded every 10 min. Fitbit proprietary algorithms provided physical activity summarized as mean number of steps per minute, which we averaged during the 10-min period following a GPS-based greenness exposure assessment. We utilized Generalized Additive Mixed Models to examine associations (every 10 min) between greenness and physical activity adjusting for neighborhood and individual socioeconomic status, Census region, season, neighborhood walkability, daily mean temperature and precipitation.

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We assessed effect modification through stratification and interaction models and conducted sensitivity analyses.

Results: Mean 10-min step count averaged 7.0 steps (SD 14.9) and greenness (NDVI) averaged 0.3 (SD 0.2). Contrary to our hypotheses, higher greenness exposure was associated non-linearly with lower mean steps per minute after adjusting for confounders. We observed statistically significant effect modification by Census region and season.

Discussion: We utilized objective physical activity data at fine temporal and spatial scales to present novel estimates of the association between mobility-based greenness and step count. We found higher levels of greenness were inversely associated with steps per minute.

1. Introduction

The explosion of research on nature and health in environmental epidemiology led to numerous studies investigating the association between exposure to greenness, or vegetation quantity, and physical activity, as well as chronic disease outcomes (Fong et al., 2018; James et al., 2015, 2016; Jimenez et al., 2021; Kaplan, 1995). Green environments have been hypothesized to be associated with higher levels of physical activity and to provide additional benefits compared to physical activity in non-green environments due to increased opportunities for physical activity and psychological restoration (Almanza et al., 2012; Coombes et al., 2010; Dewulf et al., 2016; Hillsdon et al., 2006; Kajosaari and Pasanen, 2021; Markevych et al., 2017; Mnich et al., 2019; Wheeler et al., 2010). However, previous studies examining the association of greenness with physical activity have reported inconsistent results (Klompmaker et al., 2018; Roscoe et al., 2022). Also, most of these studies used residential-based measures of exposure and self-reported measures of physical activity, making it difficult to infer true associations due to potential for measurement error (James et al., 2015; Jimenez et al., 2021).

Greenness exposure is often quantified by measuring surrounding residential greenness via satellite-derived greenness (Normalized Difference Vegetation Index) or greenspaces such as parks and gardens within a specific distance of the residential address (Fong et al., 2018; James et al., 2015; Jimenez et al., 2021). Residential exposures do not quantify exposure occurring outside of these selected distances, nor do they capture how much time an individual spends in nature, and residence-based analyses cannot be used to explore if individuals obtain their physical activity in green environments. Additionally, the appropriate scale of residential exposures is challenging to discern. Researchers remain uncertain of the true spatial and temporal boundaries exerting contextual influences (James et al., 2015). This potential source of bias is known as the Uncertain Geographic Context Problem, which remains a critical limitation of prior research studies (Chaix et al., 2012, 2013; Kwan, 2012a, 2012b, 2019; Park and Kwan, 2017) evaluating greenness as an exposure. Due to the contextual nature of environmental exposures, there is not a set spatial boundary of influence. Measures of activity space (Brokamp et al., 2016; Kwan, 2019) – a term used to describe the set of locations with which a person has direct contact during day-to-day activities (Perchoux et al., 2016) – present a solution to the Uncertain Geographic Context Problem. A growing number of studies have collected objective measures of mobility-based greenness exposure and physical activity (Almanza et al., 2012; James et al., 2017; Marquet et al., 2020, 2022a). Widespread use of mobile phone and wearable global positioning systems (GPS) technology (Markevych et al., 2017) have allowed researchers to evaluate contextual exposures using mobility-based measurements to quantify mobility-based greenness.

Using data collected from the Nurses' Health Study 3 (NHS3) Mobile Health (mHealth) Substudy participants, the aim of this intra-individual and repeated measures GPS study was to quantify associations of 10-min level mobility-based greenness exposure with aggregated 10-min level physical activity captured by a wearable device. Our aim was to determine associations between greenness exposure and physical activity using this rich source of objective data. We hypothesized that higher mobility-based greenness exposure was associated with higher mean steps-per-minute averaged over a 10-min period, after adjustment for potential confounders.

2. Methods

2.1. Population

2.1.1. Nurses' Health Study 3 (NHS3)—NHS3 began in 2010 and is an ongoing open-enrollment prospective cohort of nurses and nursing students living in the US or Canada. Participants are required to be a registered nurse, licensed practical/vocational nurse, or nursing student and to be born on or after January 1, 1965 for eligibility into the study. At the time of selection for the mHealth Substudy there were 49,693 participants enrolled in NHS3. Once enrolled, participants provide updated residential history and complete web-based questionnaires on lifestyle and medical characteristics every six months. For participants who have completed two or more questionnaires, the response rate is above 80% (Chavarro et al., 2016; Gaskins et al., 2015; Gaskins et al., 2015; Mooney and Garber, 2019).

2.1.2. NHS3 mobile health (mHealth) substudy—The NHS3 mHealth Substudy began enrollment in March 2018 and data collection was completed in February 2020 with 500 enrolled participants (Fig. 1) residing in 42 of the 48 contiguous states during the data collection period.

The mHealth Substudy required participants to be aged 21 or older on March 12, 2018 and demonstrate adherence to questionnaire completion by providing information on height, weight, physical activity, and sleep in prior NHS3 questionnaires for enrollment. As the study aimed to prospectively examine impacts of various lifestyle risk factors on sleep disturbance and Fitbit wearables have reduced accuracy in these populations, participants with a doctor-diagnosed sleep disorder were not eligible. Full study recruitment, protocol, and data collection methodology are detailed in an NHS3 protocol paper by Fore et al. (2020). In brief, mHealth participants wore a consumer-wearable fitness tracker (Fitbit™ Charge HR, Fitbit™ Charge 2 and Fitbit™ Charge 3) and downloaded a custom smartphone application on their personal smartphones for seven-day sampling periods every three months for a year from enrollment. This allowed us to capture seasonal variability in behaviors and exposures. Consistent with other mobility studies (Marquet et al., 2022b), we conducted a 7-day protocol. This time frame should capture behaviors and exposures across work and nonwork days. A mobile phone application acquired GPS location data at ~10-min intervals throughout the 7-day sampling period. We omitted daily main sleep periods from the dataset under the assumption that physical activity does not occur during sleep periods using Fitbit™-derived sleep data. We included participants who provided at least 8 hours of GPS data on at least three unique days in primary analyses (Fig. 1).

2.2. Exposure

We used the Normalized Difference Vegetation Index (NDVI) as a measure of vegetation exposure, which was linked to GPS data to create a mobility-based greenness exposure. The NDVI is the most widely used satellite-derived indicator of the quantity of photosynthesizing vegetation and has been previously used as a marker for exposure to greenness in epidemiological studies (Fong et al., 2018; James et al., 2015). NDVI ranges from − 1 to 1 with higher numbers indicating more green vegetation. NDVI values below 0 represent water, ~0 represent rocks and bare soil including concrete, and values ~0.6–0.8 represent temperate and tropical forests (Klompmaker et al., 2018). NDVI was rescaled so all values below zero were recoded to zero, so that all non-green areas were valued identically (James et al., 2017; James et al., 2016; James et al., 2017). We used Google Earth Engine Landsat specific processing methods to produce seasonal, cloud-free, Landsat 8 raster images (Appendix A). We linked these seasonal 30 m x 30 m NDVI raster images to season-matched GPS mobility data across study enrollment years 2018 and 2019.

2.3. Outcome

We used accelerometry data from Fitbit™ wearable devices (Fore et al., 2020) to summarize physical activity in mean steps-per-minute, which we averaged for 10-min interval after each GPS-greenness location. Mean steps-per-minute is preferable to raw step counts, as averages fluctuate less with fine scale missingness in GPS data (Armstrong et al., 2019; Yuenyongchaiwat, 2016).

2.4. Covariates

We identified potential confounders a priori (Fong et al., 2018; James et al., 2016; Roscoe et al., 2022). These included individual participant measures of age (years; continuous), socioeconomic status defined as: education level (masters in nursing or higher; binary), and marital status (never [never married]]/ever [married, widowed, divorced]; binary). The NHS3 cohort does not have data on household income. Area-level measures included neighborhood socioeconomic status (z-score; quartiles), walkability (z-score; quartiles), mean daily temperature (Celsius; quartiles), daily precipitation (millimeters; binary), season and Census region (Northeast, Midwest, South, West).

We obtained age, education level and marital status from the full NHS3 cohort study dataset from participants initial questionnaire return (Module 1). Module 1 predated enrollment in the Substudy. We used a composite score of 7 census tract level variables from the 2010 Census to estimate neighborhood Socioeconomic Status (nSES). Variables represented domains that have been previously associated with health outcomes, including education, employment, housing, wealth, racial composition, and population density (DeVille et al., 2023). Z-scores were summed for each variable to create a nSES score. Higher scores indicated higher nSES (i.e. less socioeconomic deprivation). We joined quartiles of nSES score using the location of each 10-min GPS point to create a mobility-based nSES.

We defined neighborhood walkability, a measure of population and business density, for each Census tract in the US as a composite 3-item score. This included z-scored intersection density calculated from 2019 Tiger/Line shapefiles of all roads with interstates removed (Bureau, 2022), population density, from 2019 ACS population data (Explore Census Data, 2022), and business density, from 2018 Infogroup US Historical Business Data (Infogroup, 2020). We summed the z-scores for each component variable (3-items) to create a neighborhood walkability index. Higher scores indicated more walkable areas. We joined quartiles of walkability score using the location of each 10-min GPS point to create a mobility-based walkability.

We obtained daily mean temperature and precipitation data at 800 m spatial resolution for the study period (2018–2020) from Parameter-elevation Regression on Independent Slopes Model (PRISM) (Luzio et al., 2008). PRISM variables were joined on date and paired GPS coordinates of each 10-min repeated measure for mobility-based measures of temperature and precipitation. We classified daily mean temperature into quartiles and dichotomized precipitation to any precipitation/no precipitation.

We defined the Census region of each GPS point as one of 4 census regions (Northeast, Midwest, South, West), and derived season (Spring (March–May), Summer (June–August) Fall (September–November), Winter (December-Febuary)) from the date (month) associated with each GPS point.

2.5. Statistical methods

Due to the intensive longitudinal nature of the dataset, we explored the possibility of nonlinear associations between mobility-based greenness exposure and physical activity using Generalized Additive Mixed Models (GAMM). We accounted for repeated measures within the same participant using a random intercept for participant. We fit NDVI using natural cubic splines with three knots using the mgcv package in R 4.1 to account for possible non-linearity. We adjusted models for the a priori selected confounders listed above. We specified an autoregressive correlation structure due to the repeated-measure, longitudinal nature of the data.

2.6. Effect measure modification

We assessed the presence of effect measure modification through models stratified on quartiles of walkability and nSES, median age (< 0.05) of effect modification we included multiplicative interaction terms. 2.7. Sensitivity analyses To address epidemiologic and geographic biases, we conducted four sensitivity analyses to test the robustness of our analyses. Fig. 3 provides a visual representation of the smartphone mobility data from participants used in this analysis and how we restricted these data for the sensitivity analyses described in detail below.

The first sensitivity analysis was designed to minimize selective daily mobility bias (Fig. 2a) (Plue et al., 2020). In mobility studies with intensive longitudinal data, this bias functions as a confounder. The phenomenon, where it is difficult to discern whether an individual is passively exposed to a space or actively seeks it, is referred to as a 'selective (daily) mobility bias'. As researchers' understanding of this bias is relatively new, it is understudied. To assess the impact of selective daily mobility bias, we restricted activity space to GPS locations within a standard deviation ellipse — subject-specific standard deviation of the x-coordinates and y-coordinates from the mean center of that subject's points, to eliminate locations outside of an individual's normal range.

We focused our second sensitivity analysis on associations during time outside of work (Fig. 2b). We omitted time at work by geocoding workplace addresses at the time of study and restricting GPS location data to locations outside of a 160-m radial buffer (0.1 mile). The size of this buffer was derived from hospital dimensions (the typical workplace of our study participants) as the majority of hospital sizes are thought to fall within this buffer size (Insights from a Healthcare Architect's Journal, 2019).

In our third analysis, we omitted datapoints that may include sedentary behaviors or driving (Fig. 2c). We used timestamps in addition to GPS locations to estimate velocity, and restricted analyses to velocities that fell between walking and running (0.8–4 m/s) to obtain datapoints of active transport or recreating (Cruciani et al., 2018).

Lastly, we restricted our cohort to 208 participants who provided at least 12 h of GPS location data daily on 5 unique days in two distinct sample periods (restricted analytical dataset) (Fig. 1). This stringent criterion maximizes the amount of data per individual across time, to support the primary analysis findings with a robust intra-individual sample.

3. Results

3.1. Descriptive

Participants in the primary analytical cohort of the NHS3 mHealth Substudy resided in 42 out of 48 states across the contiguous US (Fig. S1. After selecting participants who provided at least 8 h of GPS data daily on 3 unique days and omitting main sleep periods, the primary analytic cohort included 337 participants with 639,364 observations (Fig. 1). Each participant had on average 96.2 observations per day (SD 44.1) or approximately 16 h per day and a total of 1878 observations (SD 847.2) or approximately 313 h during the 1-year study period (Table 1). Averaged across seasons, greenness exposure was 0.31 (SD 0.2) and participants took 7.0 (SD 14.9) steps per minute (Table 2).

On average, we observed small variations by season for both the exposure and outcome with the spring months having the highest mean greenness exposure and highest average step count per minute (Table 2). Participants residing in the South had the smallest annual change in NDVI (Table 2). Similar seasonal variations were observed among the restricted dataset of 208 participants with 498,521 observations who provided at least 12 h of GPS data daily on 5 unique days in two distinct sample periods (Supplemental Table 1).

3.2. Generalized Additive Mixed Models

We observed a statistically significant non-linear association between mobility NDVI and mean steps per minute (Fig. 4).

There were three distinct relationships with inflection points at 0.2 and 0.6 NDVI. Between NDVI values of 0–0.2, higher values of NDVI were very weakly associated with greater mean steps per minute (0.8 step more per 0.1 difference in NDVI). In contrast, between NDVI values of 0.2–0.6, higher values of NDVI were associated with fewer mean steps per minute (1.0 fewer mean steps per minute per 0.1 difference in NDVI). Lastly at NDVI values above 0.6, higher values of NDVI were weakly associated with increased mean steps per minute with 0.5 step more per 0.1 increase in NDVI (Fig. 4).

3.3. Stratified analyses

We observed no evidence of effect modification by median age, race, neighborhood SES, neighborhood walkability, mean daily temperature and daily precipitation presence.

Statistically significant effect modification by both season and region were observed. Seasonal stratified analyses revealed inverse associations in the Fall, Spring and Summer with no association in the Winter (Fig. 5).

Regional differences were observed across the strata, with the Northeast and Southern regions following the pattern of the main analysis (Fig. 6). An inverse association was observed in participants residing in the Midwest and no association was observed in the West until NDVI was greater than 0.6, whereupon increasing values of NDVI were inversely associated with steps per minute (Fig. 6).

3.4. Sensitivity analyses

In sensitivity analyses attempting to restrict bias due to selective mobility, non-work location and restriction of cohort to those with more data, we did not identify any statistically significant differences from the primary analysis (Supplemental Figs. 2, 3, 4). When we restricted our analyses to active transportation velocities that fell within walking and running (Fig. 2c) as a transportation mode, we observed no association between NDVI value and steps per minute (Fig. 6).

4. Discussion

Overall, we found a small negative association of 10-min level mobility-based greenness with objectively measured mean step count per minute across the most frequent NDVI exposure range (0.2 up to 0.60). Our results expanded upon previous work on the association between greenness and physical activity at the residential level. Klompmaker et al. saw a positive relationship between residential NDVI and self-reported physical activity (Klompmaker et al., 2018) in a Dutch national health surveys, and Marquet et al. observed a positive association looking at weekly activity spaces and step counts among working adults in the US (Marquet et al., 2022b). However, our findings were the 10-min scale and attempted to assess the momentary association between greenness and physical activity, whereas previous studies examined greenness exposure over a longer timescale. Our results were consistent with those of Persson et al. (2019), in which individuals moving to greener environments had a decrease in their physical activity. Furthermore, when we restricted our analysis to walking or running physical activity data only, we did not observe an association between smartphone mobility-based greenness and steps-per-minute. This suggests that green environments may be associated with sedentary behavior but when an individual conducts physical activity, their speed does not alter across levels of NDVI. This finding supports conclusions by James et al. (James et al., 2017) who suggest walkability rather than greenness as a predominant driver of accelerometry based physical activity (Baobeid et al., 2021).

We observed evidence of effect modification across region and season. Regional differences drove associations with mild nonlinear positive associations between increases in NDVI and mean steps-per-minute observed in lowest and highest levels of NDVI in the South, and consistent negative associations observed in the Midwest. The South has the smallest seasonal change in NDVI, suggesting the positive association could be due to maintaining a green environment throughout the year.

Our results driven by fine-scale spatial and temporal data suggest that more research is needed to understand physical activity as a mechanism underlying how exposure to greenness is associated with improved health outcomes across various spatial and temporal scales, due to inconsistent results in the literature.

Our study has limitations. First, NHS3 is a cohort of predominantly upper-middle class white women nurses and as such these findings may have limited generalizability outside this population. Diverse cohorts should assess effect modification across race/ethnicity and SES to further confirm our findings. Secondly, step count as a proxy for physical activity remains another limitation, as it does not capture physical activity from weight-lifting, cycling, gardening, or swimming. However, most of the US and NHS3 participants record walking as the primary source of physical activity (CDC, 2013). Lastly, we standardized blue space to zero in our NDVI exposure, however blue space is thought to have associated health benefits like green space (Georgiou et al., 2021; White et al., 2021). Understanding how to mutually account for the two exposures is an important next step.

Our study also had a number of strengths. First, we were able to utilize a time-variant mobility greenness measure at 30 m resolution, which enabled us to identify the quantitative value of greenness at a precise moment better addressing the exposure of interest. The intensive longitudinal spatial and temporal data allowed us to quantify momentary greenness exposure and physical activity at the minute-level and conduct several analyses examining seasonal trends and potential confounders or effect modifiers of the association. Second, utilizing an objective physical activity metric instead of self-reported physical activity reduced the likelihood of recall bias in our study compared to studies that used self-reported measures of physical activity. Lastly, as the mHealth Substudy was nested within the larger NHS3 cohort, we obtained high quality data from participants and covariate data prior to collection of exposure or outcome, reducing the likelihood of misclassification.

As environmental data becomes easier to access in mass quantities, it is essential that we prioritize real time exposure data. Environmental epidemiology too often ignores consequences of the uncertain geographic context problem and defining the extent of the exposure in question (Hooper et al., 2013; Kwan, 2012b; Spiegelman, 2010). By linking fine scale spatial and temporal greenness and physical activity data, we attempt to address critical gaps in the literature and look holistically at contextual environmental exposures beyond the residential environment. In conclusion, we did not observe higher levels of physical activity in greener locations in this intensive longitudinal spatial temporal analysis. Rather, the association was nonlinear in nature and across most frequent exposure distributions, greener locations were observed to be associated with fewer steps-per-minute.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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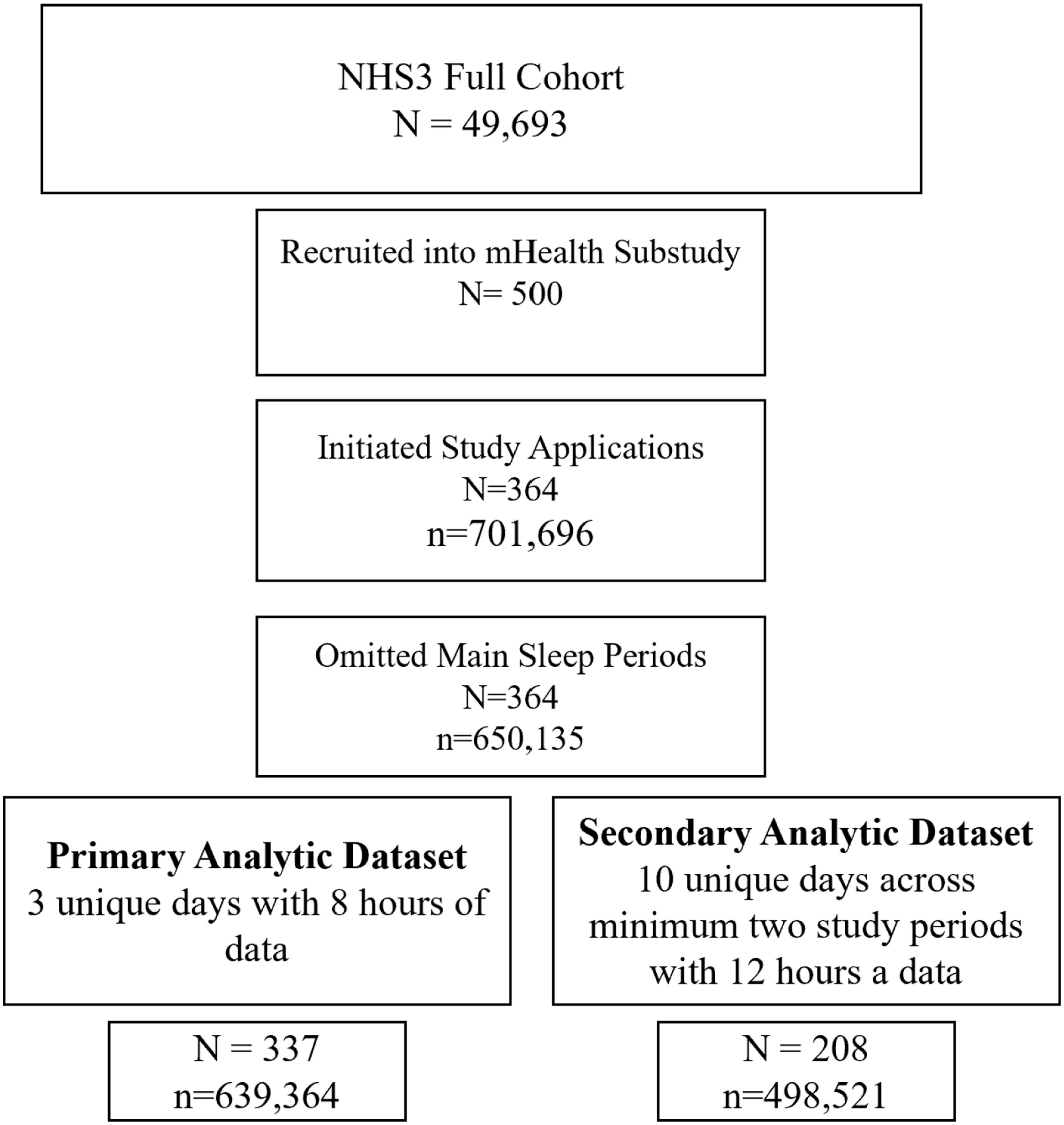

Figure 1.

Study participant flow diagram for the Nurses' Health Study 3 mHealth Substudy and restriction criteria for primary analytic dataset and secondary analytic dataset for cohort population (N) and GPS mobility observations (n).

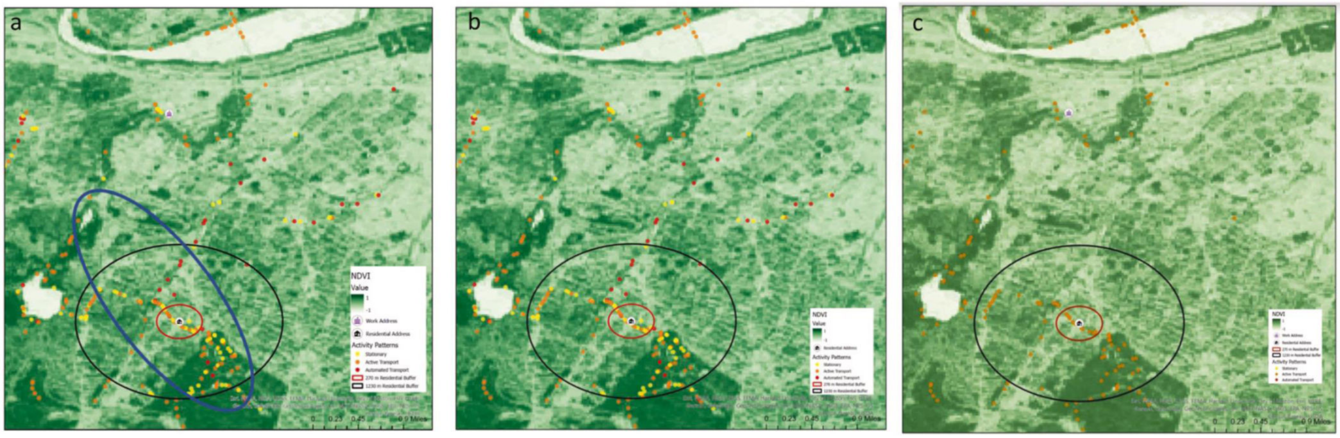

Figure 2:

Three panel exposure map* a) GPS mobility data over traditional residential buffers of 270 m and 1230 m and a selective daily mobility bias restriction criterion, b) workplace omitted GPS mobility data over traditional residential buffers, and c) active transport (walk to run velocities) GPS mobility metrics of exposure over traditional residential buffers.

*This figure does not represent participant data. Data were obtained via the author’s personal collection.

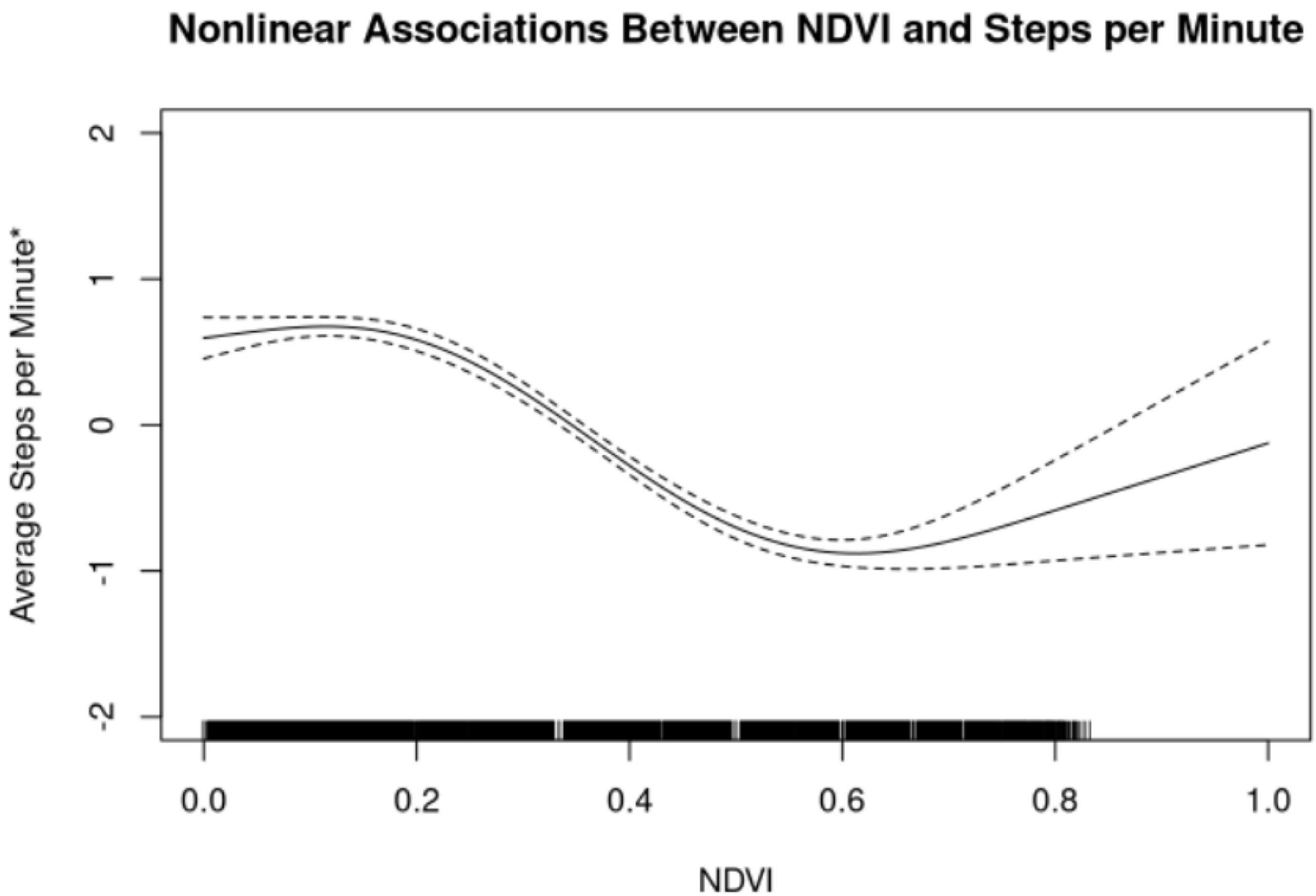

Figure 3.

Associations[a] between NDVI[b] and average steps per minute across a 10-min period.

[a] Controlling for age (years; continuous), socioeconomic status defined as: educationlevel (masters in nursing or higher; binary), and marital status (never [never married]]/ ever [married, widowed, divorced]; binary), and area-level measures of neighborhood socioeconomic status (z-score; quartiles), walkability (z-scores; quartiles), mean daily temperature (Celsius; quartiles), daily precipitation (millimeters; binary), season and Census region in the 2018–2020 Nurses' Health Study mHealth Substudy.

[b] NDVI values below 0 represent water, ~0 represent rocks and bare soil including concrete, and values ~0.6–0.8 represent temperate and tropical forests.

* Average steps per minute across each 10-min collection period.

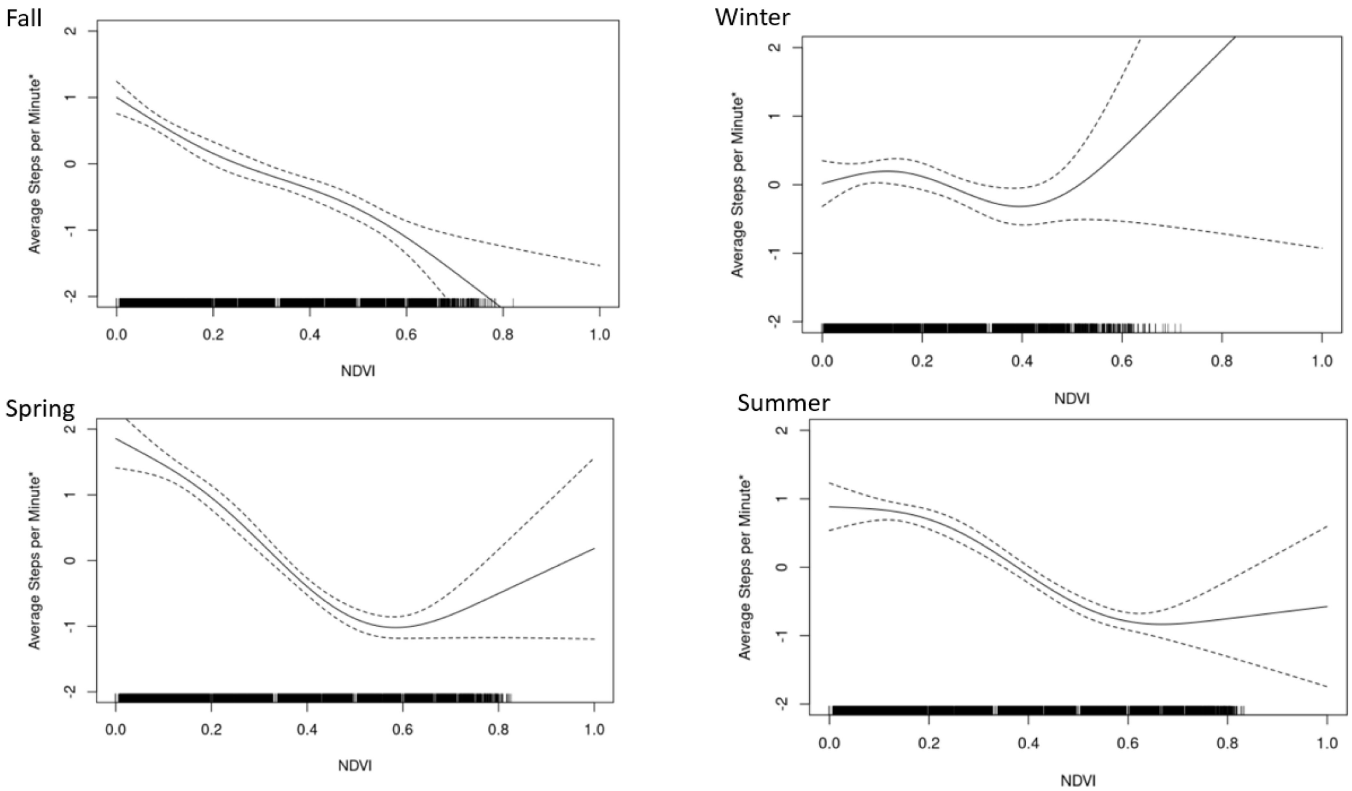

Figure 4.

Associations[a] between NDVI[b] and average steps per minute across a 10-min period stratfiying on season.

[a] Controlling for age (years; continuous), socioeconomic status defined as: education level (masters in nursing or higher; binary), and marital status (never [never married]]/ ever [married, widowed, divorced]; binary), and area-level measures of neighborhood socioeconomic status (z-score; quartiles), walkability (z-scores; quartiles), mean daily temperature (Celsius; quartiles), daily precipitation (millimeters; binary), and Census region in the 2018–2020 Nurses' Health Study mHealth Substudy.

[b] NDVI values below 0 represent water, ~0 represent rocks and bare soil including concrete, and values ~0.6–0.8 represent temperate and tropical forests

*Average steps per minute across each 10-min collection period.

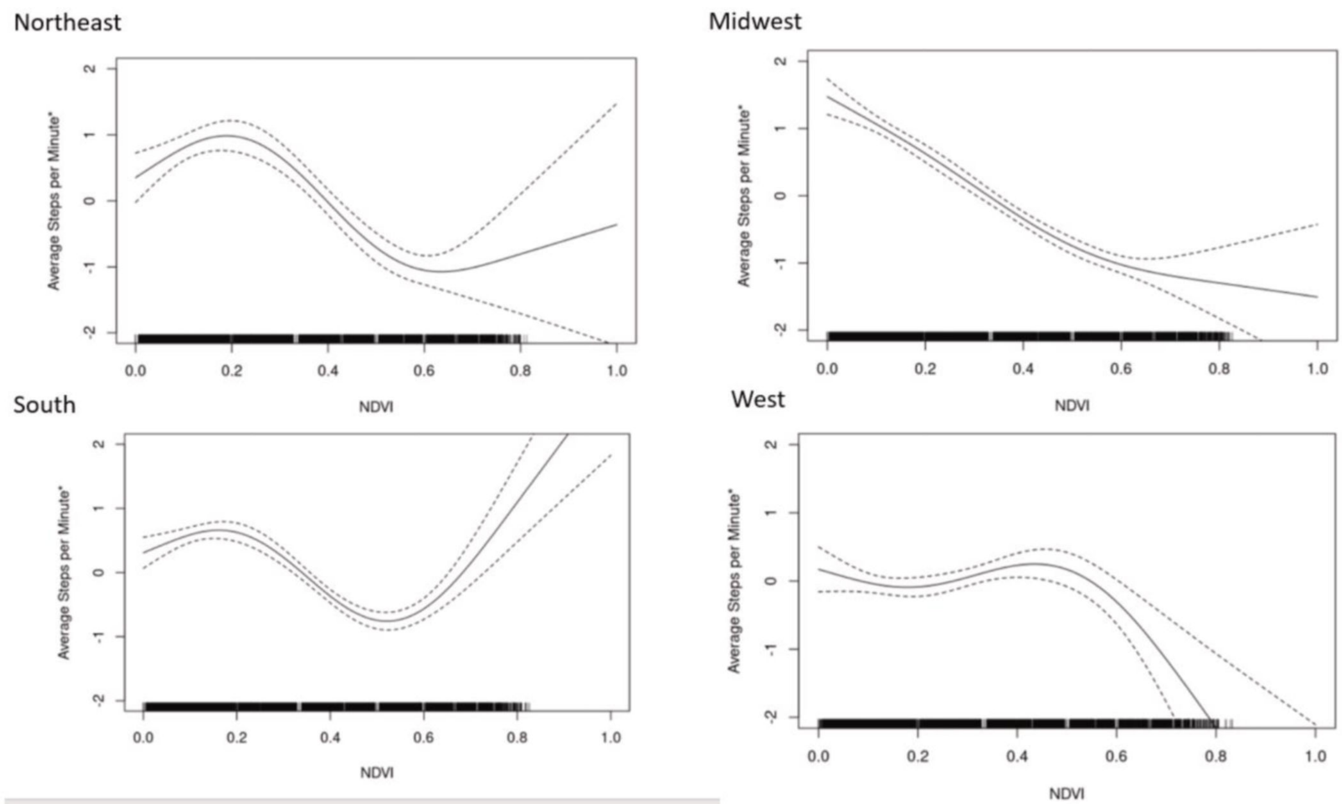

Figure 5.

Associations[a] between NDVI[b] and average steps per minute across a 10-min period stratifying on region

[a] Controlling for age (years; continuous), socioeconomic status defined as: education level (masters in nursing or higher; binary), and marital status (never [never married]]/ ever [married, widowed, divorced]; binary), and area-level measures of neighborhood socioeconomic status (z-score; quartiles), walkability (z-scores; quartiles), mean daily temperature (Celsius; quartiles), daily precipitation (millimeters; binary), and season in the 2018–2020 Nurses' Health Study mHealth Substudy.

[b] NDVI values below 0 represent water, ~0 represent rocks and bare soil including concrete, and values ~0.6–0.8 represent temperate and tropical forests

*Average steps per minute across each 10-min collection period.

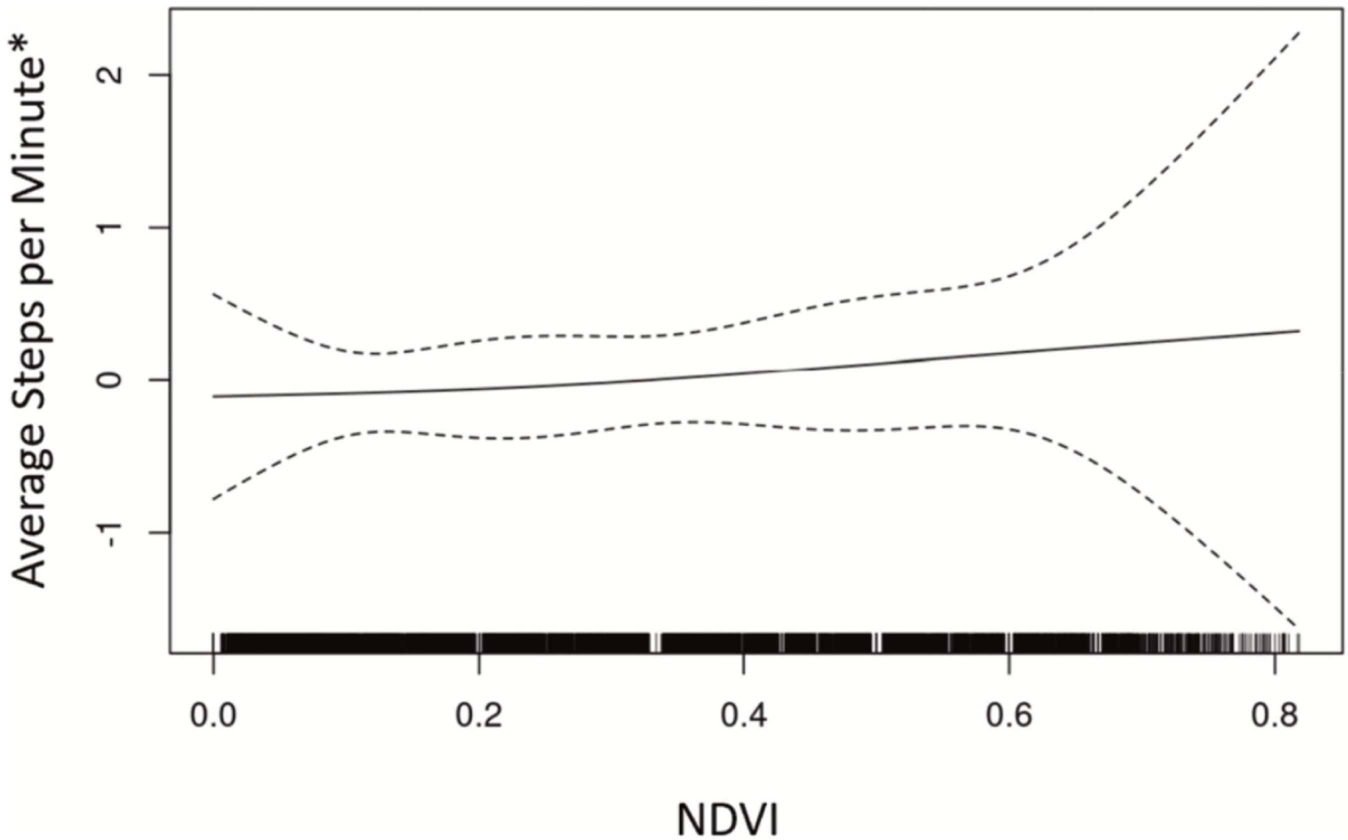

Figure 6.

Associations[a] between NDVI[b] and average steps per minute across a10-min period, restricting on active transportation (walk to run velocity) GPS mobillity data

[a] Controlling for age (years; continuous), socioeconomic status defined as: education level (masters in nursing or higher; binary), and marital status (never [never married]]/ ever [married, widowed, divorced]; binary), and area-level measures of neighborhood socioeconomic status (z-score; quartiles), walkability (z-scores; quartiles), mean daily temperature (Celsius; quartiles), daily precipitation (millimeters; binary), season, and Census Region in the 2018–2020 Nurses' Health Study mHealth Substudy.

[b] NDVI values below 0 represent water, ~0 represent rocks and bare soil including concrete, and values ~0.6–0.8 represent temperate and tropical forests

*Average steps per minute across each 10-min collection period.

Table 1.

Study demographics for the Nurses' Health Study mHealth Substudy Across Restriction Criteria.

Variable		Primary Analytic Dataset (n=337)		Secondary Analytic Dataset (n=208)	
	Variable	**N**	**% / Mean (SD)**	**N**	**%**
Age	Age	330	36.0 (7.3)	208	25.96 (7.0)
Race	White	317	94.1	192	92.3
	Black	8	1.8	6	2.9
	Asian	2	0.1	2	1
	Mixed Race	4	1.2	2	1
	Other	6	1.8	6	2.9
Ethnicity	Hispanic	14	4.2	8	3.9
Married	Yes	207	61.4	127	61.1
	No	130	38.6	81	38.9
Advanced Degree	Yes	88	26.1	52	25
	No	249	73.9	156	75
Employment	Yes	319	96.7	203	97.6
	No	11	3.4	5	2.4
Variable		**Main Study Observations (n=639,364)**		**Restricted Study Observations (n=498,521)**	
Walkability	Mean	637,505	−0.02 (2.5)	496,962	−0.06 (2.4)
nSES	Mean	636,476	1.6, (3.3)	496,283	1.7 (3.3)
Temperature	Mean	604,911	15.1 (10.0)	466,207	15.0 (10.0)
Precipitation	Mean	604,911	3.4 (9.0)	466,207	3.3 (8.9)
Greenness	Mean	639,364	0.3 (0.2)	498,521	0.3 (0.2)
Seasonality	Fall	167,871	26.3	134,660	27
	Winter	127,860	19.9	103,797	20.8
	Spring	136,117	21.3	105.248	21.1
	Summer	207,496	32.4	154,816	31.1

Table 2.

Participant Greenness and Physical Activity Distributions Across Seasons

	N	Steps/Min Mean (SD)	Steps/Min Min, Max	Greenness Mean (SD)	Greenness Min Max
Total Participants	337	7.04 (14.93)	0.00, 263.78	0.31 (0.21)	0.00, 0.84
Fall	277	6.76 (14.62)	0.00, 181.00	0.27 (0.20)	0.00, 0.82
Winter	252	6.60 (14.25)	0.00, 183.13	0.21 (0.15)	0.00, 0.73
Spring	202	7.43 (15.44)	0.00, 219.00	0.37 (0.20)	0.00, 0.84
Summer	283	7.27 (15.19)	0.00, 263.78	0.37 (0.21)	0.00, 0.84