



Exposure to greenness and physical activity behavior: A longitudinal GPS and accelerometry study before and after retirement

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ABSTRACT

Background: Higher residential greenness seems to be associated with more physical activity (PA), but it remains unclear whether exposure to greenness outside the residential area associates with PA. Therefore, we investigated the association between activity space greenness and PA before and after retirement.

Methods: This longitudinal study is based on data from the Finnish Retirement and Aging study (FIREA). We included participants with at least two valid (≥ 10 -h) days of accelerometer and GPS measurement (SenseDoc 2.0) both before and after retirement ($n = 123$, mean age 63.3 [SD 1.0] years, 82 % women). PA was expressed as light, moderate-to-vigorous (MVPA), total PA, and transportation PA. Activity space for each participant and time-weighted exposure to greenness was calculated using GPS-data and normalized difference vegetation index (NDVI) from satellite images. Cross-sectional associations between exposure to greenness and PA were examined on workdays and days off before retirement and on retirement days. Longitudinal changes in PA from workday to retirement day were analyzed in the exposure to greenness change groups (low, high, increase, or decrease).

Results: On workdays but not on days off or retirement, higher exposure to greenness was associated with less MVPA [$\beta = -0.23$ (95% CI: 0.44, 0.02)] and transportation PA [$\beta = -0.27$ (-0.47, -0.08)]. MVPA and transportation PA increased among all participants from workday to retirement [6.1 (1.7, 10.5) min/day, and 7.8 (3.6, 11.9) min/day, respectively]. However, the changes in exposure to greenness were not associated with the changes in light PA, MVPA, or transportation PA.

Conclusion: While higher exposure to greenness based on NDVI was associated with less MVPA and transportation PA on workdays, the changes in exposure to greenness were not associated with the changes in PA.

1. Introduction

Insufficient physical activity (PA) contributes to the global burden of non-communicable diseases, many of which could be prevented with regular and sufficient PA (Santos et al., 2023). PA behavior is affected by multiple individual, social, and environmental factors, including availability and accessibility of green areas (Bauman et al., 2012). Exposure to green areas, or greenness, has been associated with better mental and physical health (Gonzales-Inca et al., 2022; Halonen et al., 2014; James et al., 2015; Jimenez et al., 2021; Kivimäki et al., 2021), and PA has been suggested as one of the mechanisms mediating the health effects of

exposure to greenness (Richardson et al., 2013; Zhang et al., 2018). Moreover, because environmental greenness affects at the population level, not just individuals, green area planning could be a cost-effective way to promote PA and public health.

Several cross-sectional studies have shown that higher residential greenness associates with higher PA (Li et al., 2008; Mytton et al., 2012; Puhakka et al., 2020; Villeneuve et al., 2018), although some opposing results exist (Maas et al., 2008; Ord et al., 2013). Moreover, few longitudinal studies have reported that higher residential greenness associates with either increasing or maintaining PA behavior (Pasanen et al., 2022; Sugiyama et al., 2013), although this association may be present

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only in women (Van Beek et al., 2024). However, a major limitation in most of these studies is the reliance on subjective questionnaire-based estimates of PA (Li et al., 2008; Maas et al., 2008; Mytton et al., 2012; Ord et al., 2013; Sugiyama et al., 2013; Van Beek et al., 2024; Villeneuve et al., 2018) rather than objective accelerometer-measured PA (Halonen et al., 2020; Pasanen et al., 2022).

Importantly, assessing only residential greenness may not capture the actual exposure to green areas, as individuals spend time and are physically active also outside their residential area (Hurvitz et al., 2014). For example, working adults may be physically active during commuting and on workdays, most daytime is spent away from home (Pasanen et al., 2021). On the other hand, on days off or during retirement there are greater possibilities to freely choose where to move (Pasanen et al., 2024). To address the limitations of assessing only residential greenness, studies have employed the concept of activity space – a dynamic, individualized representation of the geographical area a person moves through during daily life, including visited locations and the travel paths between them (Chaix et al., 2009; Schönfelder and Axhausen, 2003). Activity space provides a more accurate account of environmental exposures by considering the actual spatial and temporal patterns of behavior. Using global positioning system (GPS) tracking enables mapping activity space and linking it to environmental data such as satellite-based greenness measures (e.g., Normalized Difference Vegetation Index; NDVI), while objectively measuring PA using accelerometers (Boakye et al., 2021; James et al., 2017; Marquet et al., 2022; Tamura et al., 2019; Wilt et al., 2023). Therefore, assessing activity space greenness provides a more accurate estimate of the overall exposure to greenness compared to residential greenness.

Cross-sectional studies using this GPS-based approach have reported associations between higher activity space greenness and higher PA (Boakye et al., 2021; James et al., 2017; Marquet et al., 2022; Tamura et al., 2019), although one study from the US reported an inverse association between momentary NDVI and step count in nurses (Wilt et al., 2023), which might reflect the high step count associated with the nurses' occupation. Yet, these studies have not quantified the total daily exposure to greenness in relation to the time spent in different locations within the activity space. To account for the varying durations of exposure within the activity space an individualized residential exposure model (IREM) has been developed (Hasanzadeh et al., 2018). However, the IREM has previously been used to assess greenness exposure only with survey-based data. In this study, for the first time, we combine the IREM method with GPS-based individualized activity space and NDVI-measured greenness to obtain a spatiotemporally accurate measure of total daily exposure to greenness.

The previous studies on activity space greenness and PA have included adults of varying ages (19–82 years) (James et al., 2017; Tamura et al., 2019) and employment statuses (from 50% full time employment and 17% retired to 97% being employed) (James et al., 2017; Wilt et al., 2023). Since factors like age, employment status, and even day type (workday vs. day off) influence PA behavior (Pasanen et al., 2021; Pulakka et al., 2019), and since cross-sectional designs do not allow for causal inference, there is a need for longitudinal studies which would follow the same people over time and examine how their PA behavior changes in respect to their activity environment.

Health behaviors, including PA, are usually relatively stable over time, but life transitions such as retirement appears to shape PA behavior and time spent in different locations (Barnett et al., 2012; Pasanen et al., 2021; Pulakka et al., 2020; Stenholm et al., 2016; Vanswevelt et al., 2022). Because statutory retirement is not dependent on health and it induces changes in environmental exposure, transition to retirement can be utilized as a natural experiment setting to examine how within-individual changes in exposure to greenness are associated with PA behavior. Additionally, the freedom to choose the locations for PA is increased when work-related spatial and time use constraints are removed in the transition to statutory retirement.

To advance the knowledge on the associations between exposure to

greenness and PA, we utilized NDVI-based measures of greenness in GPS-measured activity spaces and accelerometer-measured PA behavior to investigate 1) the cross-sectional associations between exposure to greenness and PA behavior on workdays, days off, and retirement days, and 2) the longitudinal associations between changes in exposure to greenness and changes in PA behavior before and after retirement. We hypothesize that higher exposure to greenness would associate with higher PA. Due to increased leisure time and freedom to choose activity locations on retirement, we hypothesize that the association would be stronger on retirement.

2. Materials and methods

The data in this study consists of the clinical substudy of the Finnish Aging and Retirement Study (FIREA), which was conducted in Southwest Finland between 2015 and 2022. Detailed descriptions of the FIREA cohort and participant selection have been published previously (Stenholm et al., 2023). Shortly, the participants were first contacted 18 months before their estimated retirement date by sending them a questionnaire. After responding to the questionnaire, Finnish-speaking participants whose estimated retirement date was between 2017 and 2019, who lived in Southwest Finland and were still working, were invited to participate in the clinical substudy ($n = 773$). Of them, 290 agreed to participate. Thereafter, study participants were followed up with annual measurements including questionnaires, and GPS and accelerometer measurement. To determine the timing of retirement, the actual retirement date was inquired during each phase of the data collection, and this information was used to determine pre-retirement and post-retirement measurements. The participant selection flow chart is presented in [Supplementary Fig. 1](#).

The Ethics Committee of the Hospital District of Southwest Finland (84/1801/2014) approved the study. All participants gave their written informed consent before participating, and the Declaration of Helsinki was followed.

For the current analyses, we included 123 participants from the FIREA clinical substudy who had at least two valid days of accelerometer and GPS-measurement before and after retirement and who had not relocated during the follow-up. Moreover, all of our participants had their home addresses within the Southwest Finland region. Participants with no GPS data outside the home location were excluded.

2.1. Physical activity assessment

We used the kernel-based algorithm developed by Thierry et al. (2013) to identify different intensity PA in different locations and during trips from the raw GPS and accelerometer data. The software used in data download and processing was SenseAnalytics (versions 1.9 and 1.10), ArcGIS (version 10.3.1), Python (version 3.6.6), R (version 3.5.3), and PostgreSQL (version 11.1) with PostGIS extension.

PA was monitored using a waist-worn triaxial accelerometer with an inbuilt GPS sensor (SenseDoc 2.0, Mobysens Technologies Inc., Canada), as described in detail earlier (Pasanen et al., 2023). A study nurse instructed the participants during the clinical examination visit to wear the device during waking hours except when the device could be exposed to water. Before retirement, the participants were instructed to wear the device on at least two workdays and two days off, and a minimum of four measurement days was instructed after retirement. To distinguish workdays and days off, the participants were instructed to fill a diary. Non-wear time was identified based on accelerometer data using the Choi method which identifies non-wear time as consecutive zero counts within a 90-min time window allowing a 2-min interval of non-zero counts with the up or downstream in 30 min consecutive zero counts window (Choi et al., 2011). A valid measurement day was defined as wear time of ≥ 10 h during waking hours. Participants with at least one valid workday and day off measurement days before retirement and two valid measurement days on retirement were included in

the analyses. The combined GPS and accelerometer measurements were performed on the same season before and after retirement for each participant, although the measurements were conducted during all seasons.

The raw accelerometry data was converted to ActiGraph equivalent counts in R (version 3.5.3) (GitHub, 2022). The counts were analyzed as counts per minute, and classified as light PA (100–2020 counts/min) (Loprinzi and Brosky, 2014; Wolff-Hughes et al., 2015) or moderate-to-vigorous PA (MVPA; >2020 counts/min) (Troiano et al., 2008). Further, total PA was calculated by summing up light PA and MVPA. Finally, to calculate transportation PA (i.e., PA when moving from a location to another or during a round trip), we used the GPS-data to identify trips that had a mean speed of <20 km/h. Then, total PA (which includes both light PA and MVPA) that took place during a detected trip with <20 km/h speed was calculated (Pasanen et al., 2023). Hereafter, this activity is referred to as transportation PA.

2.2. GPS-based individualized activity space

The GPS coordinates were recorded at 1-s intervals. The kernel bandwidth was 100 m with maximum interpolation delay of 2 min, drop time of 60 min and distance of 100 m. We used the GPS data to localize all spatial points which the individual visited (i.e., home location, visit locations, and track points during transportation). Trip and visit locations >75 km outside the Southwest Finland region were excluded (Fig. 1). This allowed us to depict an activity space which reflects day-to-day behaviors.

We used individual-level GPS tracking data to model activity spaces by adapting the IREM (Hasanzadeh et al., 2018) to account for actual mobility patterns and time-weighted exposure. Unlike traditional models that define exposure based solely on residential locations, this approach incorporates both where and how long individuals spend time during their daily activities, providing a more realistic representation of

environmental exposure.

First, each GPS point was time-weighted to reflect the duration of exposure at that location. For example, traveling by car results in short exposure periods at each track point due to higher speed, whereas walking results in longer exposure at each point. Similarly, staying at a destination for an extended period contributes more significantly to the overall exposure estimate. Based on these time-weighted points, we applied an inverse distance function to generate a continuous surface representing exposure intensity across space. This resulted in a raster surface composed of 50 m × 50 m cells, where each cell value indicates the magnitude of exposure at that location. A search radius of 150 m was used to include neighboring points in the interpolation. This captured the immediate environment within which the individual perceives and interacts with the surroundings during their everyday mobility (Laatikainen et al., 2018). The model was implemented using Esri ArcGIS ModelBuilder, and an example output is shown in Fig. 2. Activity space rasters were produced separately for three scenarios for each participant: workdays, days off, and retirement days (Fig. 3), allowing for comparison across different daily routines and life stages.

2.3. Greenness exposure

Greenness within the GPS-based individualized activity space was assessed using the NDVI from Sentinel 2 multispectral satellite images (10 m pixel size). The images were obtained in the summer of 2018 and 2019. By using summertime NDVI, we aim to better capture vegetation cover and density rather than solely greenness level, which is more sensitive to seasonal variation. We also assume that interannual NDVI variability at a given location is smaller than the variability in greenness exposure arising from participants' spatial displacement. The mean exposure to greenness was quantified by using the time-weighted GPS-based activity space and the NDVI within the activity space. As a result, we obtained the mean exposure to greenness for each participant on all

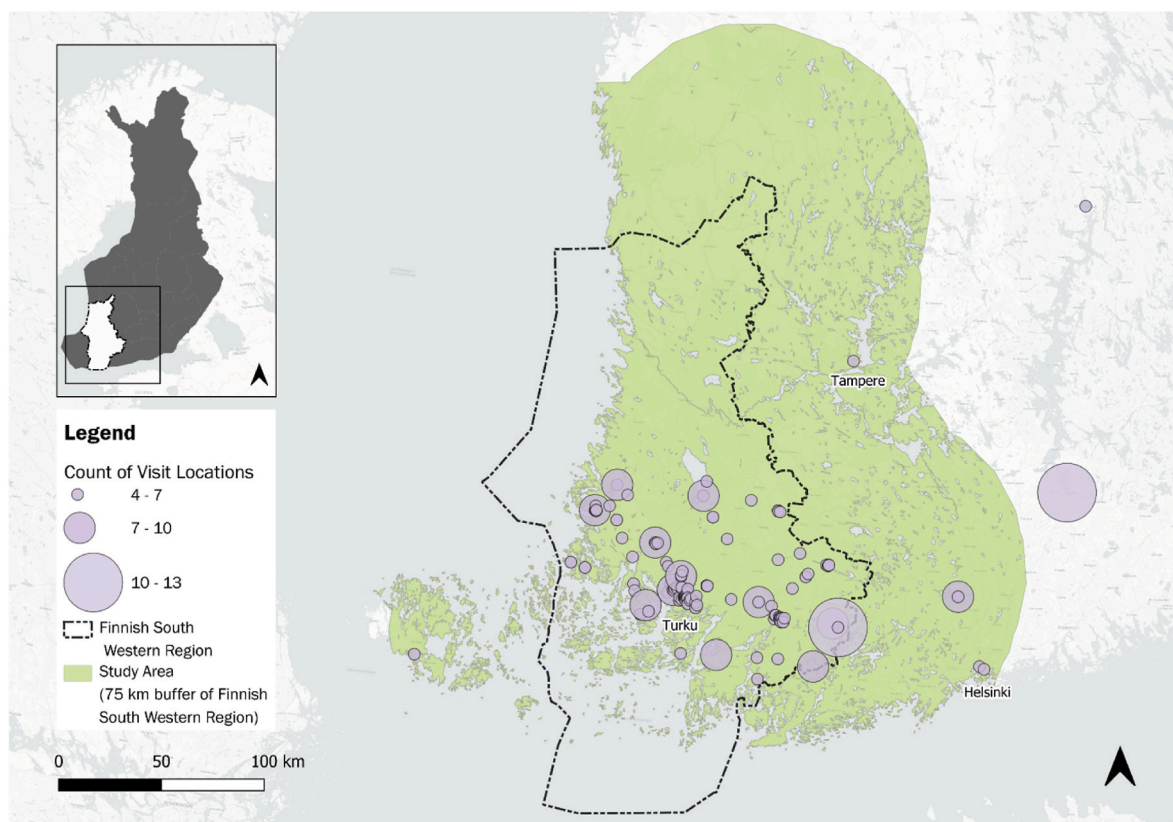


Fig. 1. Visit locations of the study participants. Locations with less than four visits have been removed from the figure to protect privacy.

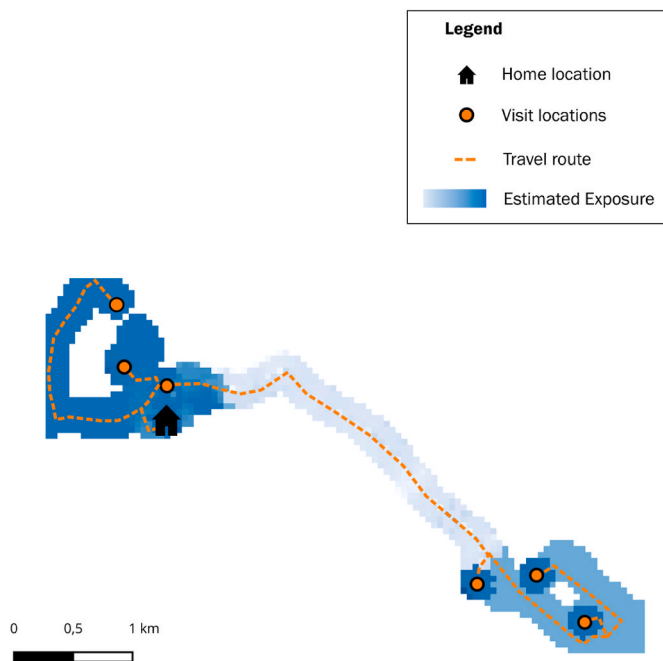


Fig. 2. Activity space modelling output.

three day types (i.e., workdays, days off, and retirement days).

2.4. Covariates and participant characteristics

Age, gender, and occupation were retrieved from the Keva Public Sector Pensions register. Occupation was classified as non-manual or manual according to the International Standard Classification of Occupations (ISCO; classes 1–4 and 5–9, respectively). Body weight and height were measured at the clinical examination visit, and body mass index was calculated. Mobility limitations (yes/no) were defined as self-perceived difficulties in walking 2 km. Marital status (married or cohabiting/not married) was obtained from the baseline questionnaire.

Residential area (750 m × 750 m square around home address)

population count was obtained from Statistics Finland. To assess the degree of residential surrounding green space, we linked the participants' home address to the mean NDVI calculated for each 750 m × 750 m grid area from a satellite image composite using Google Earth Engine, as described previously (Kivimäki et al., 2021). Home address' rurality defined using the Finnish Environment Institute's classification (Syke, 2023) and categorized as urban (classes 1–3) or rural (4–7). The season (spring, summer, autumn, or winter) for each GPS/accelerometer measurement was recorded.

To assess the representativeness of the analytical sample, we used information on self-reported PA. Weekly PA was calculated as metabolic equivalent of task hours per week (MET-h/week) from a question on average weekly duration and intensity of leisure and commuting PA (Kujala et al., 1998; Leskinen et al., 2018).

2.5. Statistical methods

Participant characteristics before retirement are presented as mean (standard deviation; SD), frequency (percentage), or median (interquartile range; IQR) as appropriate.

To analyze the cross-sectional associations between exposure to greenness and PA behavior on each day type (workday, day off, and retirement), we used linear regression analyses adjusted for age, gender, occupation, accelerometer wear time (except when analyzing transportation PA), measurement season (as a nominal, four-category variable), and residential area population count.

For the longitudinal analyses, the participants were categorized into four groups based on the change in exposure to greenness from workday to retirement: 1) continuously low (n = 31), 2) increase (n = 31), 3) continuously high (n = 43) or 4) decrease (n = 18) in exposure to greenness. The high/low division was done using the workday median exposure to greenness (NDVI 0.46), which resulted in relatively even-sized groups. Baseline characteristics of the high and low exposure to greenness groups are presented in Supplementary Table 1. The change was calculated only from workday to retirement, because the exposure to greenness and PA on days off was similar to retirement [mean NDVI 0.486 and 0.487 (ANOVA p = 0.94) and total PA 295 min and 296 min (p = 0.93) on days off and retirement, respectively]. Baseline differences in the greenness change groups were analyzed using Fisher's exact test

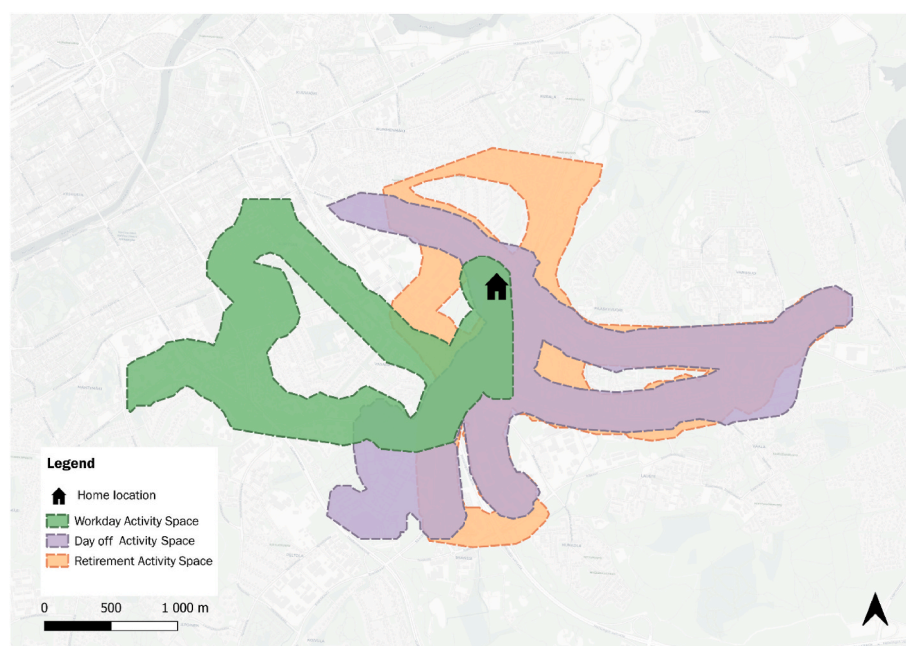


Fig. 3. Activity space for an individual across workday, day off and retirement. Home location of the individual has been anonymized to protect privacy.

for categorical variables, analysis of variance for continuous variables, and the median test for non-normally distributed continuous variables. Generalized estimating equations (GEE) with exchangeable covariance structure were used to analyze the changes in PA in each exposure to greenness change groups. This modelling takes into account the intra-individual correlation of repeated measurements. Day type (workday or retirement day), change in exposure to greenness group, and their interaction were included in the model. The models were adjusted for age, gender, occupation, accelerometer wear time (except when analyzing transportation PA), measurement season, and residential area population count. The normality of the residuals was evaluated visually.

Four types of sensitivity analyses were performed. First, we stratified the cross-sectional regression models by gender and occupation (manual/non-manual). Second, we performed the longitudinal GEE analyses only with the participants who were not living in a rural area (n = 80). Third, the longitudinal analyses were replicated by additionally adjusting for residential area greenness. Fourth, the longitudinal analyses were performed in only women (n = 101). The statistical analyses were conducted using SAS (9.4. for Windows, SAS Institute, Inc. Cary, North Carolina).

3. Results

The majority of the participants were women (82 %) and worked in a non-manual occupation (68 %) (Table 1). Having a manual occupation was most prevalent in the continuously high exposure to greenness

group (51 %) and least prevalent in the continuously low exposure to greenness group (10 %). Most participants had no mobility limitations (92 %).

Characteristics of the analytical sample, FIREA clinical substudy population, and the FIREA survey population are presented in Supplementary Table 2. Compared to the whole survey population, the analytical sample in this study was more physically active, had slightly lower body mass index, and had a lower prevalence of mobility limitations, but no marked differences were observed for sociodemographic and environmental characteristics.

3.1. Cross-sectional associations

Exposure to greenness was not associated with PA on days off or on retirement, but 0.1 NDVI units higher exposure to greenness was associated with approximately 3.7 (95% CI: 0.3, 7.0) minutes less MVPA and 4.9 (1.9, 8.0) minutes less transportation PA on workdays (Table 2).

3.2. Longitudinal associations

The associations between changes in exposure to greenness and changes in PA behavior before and after retirement are presented in Fig. 4 and Table 3. MVPA and transportation PA increased among all participants [6.1 (95% CI: 1.7, 10.5) min/day, p = 0.01, and 7.8 (3.6, 11.9) min/day, p = 0.0003, respectively], but the change was not different in the exposure to greenness change groups (interaction day

Table 1
Characteristics before retirement of all participants and by subgroups according to the changes in exposure to greenness.

	All participants (n = 123)	Continuously low exposure to greenness (n = 31)	Increase in exposure to greenness (n = 31)	Continuously high exposure to greenness (n = 43)	Decrease in exposure to greenness (n = 18)	p-value for group differences
Gender, n (%)						0.58
Women	101 (82)	25 (81)	28 (90)	34 (79)	14 (78)	
Men	22 (18)	6 (19)	3 (10)	9 (21)	4 (22)	
Age, years, mean (SD)	63.3 (1.0)	63.1 (1.0)	63.2 (0.6)	63.1 (1.2)	63.1 (1.3)	0.94
Occupation, n (%)						0.002
Manual	39 (32)	3 (10)	8 (26)	22 (51)	7 (39)	
Non-manual	84 (68)	28 (90)	23 (74)	21 (49)	11 (61)	
Marital status, n (%)						0.39
Married or cohabiting	97 (79)	23 (74)	22 (71)	37 (86)	15 (83)	
Single/widow	26 (21)	8 (26)	9 (29)	6 (14)	3 (17)	
Mobility limitations, n (%)						0.80
No	113 (92)	29 (94)	27 (87)	40 (93)	17 (94)	
Yes	10 (8)	2 (6)	4 (13)	3 (7)	1 (6)	
BMI, kg/m², mean (SD)	25.8 (4.5)	24.5 (4.8)	26.7 (5.9)	26.1 (3.7)	25.6 (2.7)	0.26
Residential population density, median (IQR), 750×750 m area	532 (957)	1038 (1441)	569 (758)	246 (460)	707 (1351)	<0.0001
Urban-rural residence, n (%)						<0.001
Urban	80 (65)	29 (94)	22 (71)	17 (40)	12 (67)	
Rural	43 (35)	2 (6)	9 (29)	26 (60)	6 (33)	
Measurement season, n (%)						0.74
Spring	40 (33)	12 (39)	11 (35)	13 (30)	4 (22)	
Summer	24 (20)	6 (19)	6 (19)	8 (19)	4 (22)	
Autumn	31 (25)	8 (26)	10 (32)	9 (21)	4 (22)	
Winter	28 (23)	5 (16)	4 (13)	13 (30)	6 (33)	
Number of valid measurement days, mean (SD)						
Workdays	3.0 (1.6)	2.8 (2.1)	3.2 (1.7)	2.9 (1.4)	3.0 (1.5)	0.88
Day off	2.9 (1.7)	2.9 (1.7)	2.6 (1.5)	3.2 (1.9)	2.8 (1.7)	0.53
Retirement	4.7 (2.1)	4.5 (1.8)	4.7 (2.0)	4.6 (2.3)	5.1 (2.3)	0.77
Accelerometer wear time, min/day, mean (SD)						
Workday	840 (80)	826 (79)	850 (92)	837 (74)	855 (72)	0.53
Day off	779 (85)	755 (85)	802 (80)	783 (84)	892 (88)	0.17
Retirement	807 (75)	815 (77)	808 (80)	808 (76)	792 (68)	0.77
Activity space on workdays, median (IQR) km²	8.1 (13.5)	5.8 (10.2)	6.2 (12.9)	10.2 (15.5)	11.2 (10.6)	0.013
Exposure to greenness on workdays, NDVI, mean (SD)	0.45 (0.12)	0.33 (0.10)	0.38 (0.06)	0.56 (0.07)	0.53 (0.05)	<0.0001

Group differences analyzed using Fisher's exact test for categorical variables, analysis of variance for normally distributed continuous variables, and the median test for non-normally distributed continuous variables. BMI = body mass index, NDVI = normalized difference vegetation index.

Table 2
Cross-sectional associations between exposure to greenness and physical activity on workdays, days off and retirement.

	Workday		Day off		Retirement	
	β (95 % CI)	p	β (95 % CI)	p	β (95 % CI)	p
Total PA	0.07 (-0.09, 0.24)	0.39	0.11 (-0.05, 0.27)	0.18	0.09 (-0.09, 0.27)	0.32
MVPA	-0.23 (-0.44, -0.02)	0.03	-0.03 (-0.21, 0.15)	0.75	-0.03 (-0.22, 0.16)	0.75
Light PA	0.12 (-0.04, 0.28)	0.13	0.13 (-0.04, 0.29)	0.13	0.11 (-0.07, 0.28)	0.24
Transportation PA	-0.27 (-0.47, -0.08)	0.007	-0.11 (-0.29, 0.07)	0.22	-0.12 (-0.30, 0.05)	0.17

Adjusted for gender, age, occupation, measurement season, residential area population density, and accelerometer wear time (except for transportation PA). PA = physical activity, MVPA = moderate-to-vigorous physical activity. The β estimate represents the change in the outcome variable if the predictor (exposure to greenness) increases by one standard deviation.

type \times change in exposure to greenness $p = 0.11$ and $p = 0.96$, respectively). Participants in the continuously low exposure to greenness group tended to have the highest transportation PA, whereas participants in the continuously high exposure to greenness group tended to have the lowest transportation PA ($p = 0.06$).

3.2.1. Sensitivity analyses

The cross-sectional associations between workday exposure to greenness, MVPA and transportation PA remained statistically significant only in women when stratified by gender. Moreover, 0.1 NDVI units higher workday exposure to greenness was associated with 14 (-0.2, 28) min/day higher light PA among women but not in men (Supplementary Table 3). Furthermore, when the cross-sectional

analyses were stratified by occupation, the association between workday exposure to greenness and MVPA was observed only in non-manual workers. Additionally, 0.1 NDVI units higher workday exposure to greenness was associated with 14 (1, 27) min/day higher light PA and 0.1 NDVI units higher exposure to greenness on days off was associated with 10 (1, 20) min/day higher light PA among non-manual workers (Supplementary Table 4).

When the longitudinal association analyses were replicated in only participants living in an urban area ($n = 80$; Supplementary Fig. 2), the results remained practically identical to the main analyses. However, the increase in MVPA was no longer significant ($p = 0.27$), and the difference in transportation PA between the continuously low and high exposure to greenness groups was not statistically significant ($p = 0.14$). Additionally adjusting the main longitudinal analyses for residential area greenness did not change the results (Supplementary Table 5). Finally, when the longitudinal analyses were performed with only women, the results remained similar to the main analyses (Supplementary Fig. 3).

4. Discussion

In this study, we found that in a predominantly female Finnish cohort of late middle-aged adults, higher exposure to greenness was cross-sectionally associated with less MVPA and transportation PA on workdays, but not on days off or on retirement days. However, we found no associations between the changes in exposure to greenness and changes in PA upon transition to retirement. To our best knowledge, this is one of the first longitudinal studies to utilize device-based measures of activity space greenness exposure and PA behavior. Therefore, this study has both important practical and methodological implications.

4.1. Cross-sectional findings

Our cross-sectional finding of the association between higher exposure to greenness on workdays and less MVPA and transportation PA is

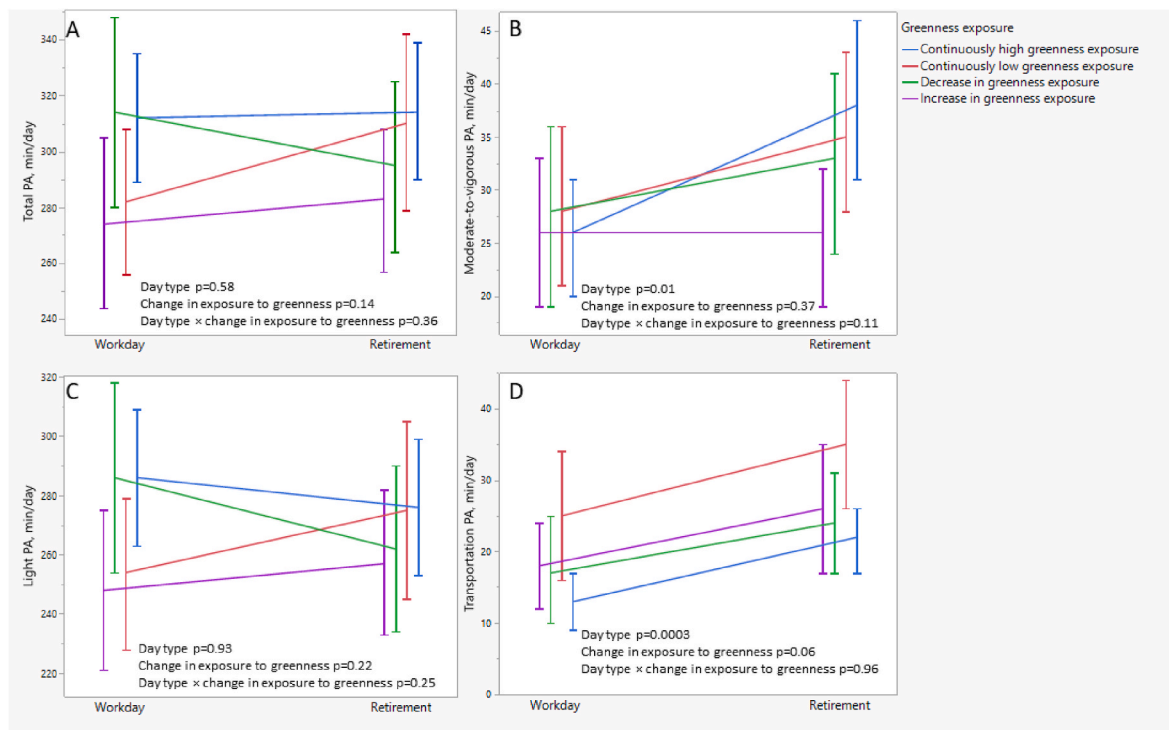


Fig. 4. Changes in physical activity by changes in greenness exposure before and after retirement. Panel A) total physical activity, B) moderate-to-vigorous physical activity, C) light physical activity, and D) transportation physical activity.

Table 3
Changes in physical activity by changes in exposure to greenness from workday to retirement.

Activity type	Group	Workday, h:min/day (95% CI)	Retirement, h:min/day (95% CI)	Mean change, min/day (95% CI)	p for group × time interaction
Total PA	All participants	4:55 (4:41, 5:09)	5:01 (4:47, 5:15)	5.2 (−13.1, 23.5)	0.36
	Continuously low	4:42 (4:16, 5:08)	5:10 (4:39, 5:42)	28.2 (−3.0, 58.8)	
	Increase	4:34 (4:04, 5:05)	4:43 (4:17, 5:08)	9.0 (−28.2, 45.0)	
	Continuously high	5:12 (4:49, 5:35)	5:14 (4:50, 5:39)	3.0 (−28.8, 34.2)	
	Decrease	5:14 (4:40, 5:48)	4:55 (4:24, 5:25)	−19.2 (−58.8, 22.2)	
MVPA	All participants	0:27 (0:23, 0:30)	0:33 (0:29, 0:37)	6.1 (1.7, 10.5)	0.11
	Continuously low	0:28 (0:21, 0:36)	0:35 (0:28, 0:43)	7.2 (0.0, 15.0)	
	Increase	0:26 (0:19, 0:33)	0:26 (0:19, 0:32)	0.0 (−7.2, 6.0)	
	Continuously high	0:26 (0:20, 0:31)	0:38 (0:31, 0:46)	13.2 (4.2, 21.0)	
	Decrease	0:28 (0:19, 0:36)	0:33 (0:24, 0:41)	4.8 (−4.8, 15.0)	
Light PA	All participants	4:28 (4:15, 4:42)	4:28 (4:15, 4:41)	−0.8 (−17.6, 16.0)	0.25
	Continuously low	4:14 (3:48, 4:39)	4:35 (4:05, 5:05)	21.0 (−9.0, 51.0)	
	Increase	4:08 (3:41, 4:35)	4:17 (3:53, 4:42)	9.0 (−25.8, 45.0)	
	Continuously high	4:46 (4:23, 5:09)	4:36 (4:13, 4:59)	−10.2 (−37.8, 19.2)	
	Decrease	4:46 (4:14, 5:18)	4:22 (3:54, 4:50)	−24.0 (−58.8, 12.0)	
Transportation PA	All participants	0:19 (0:15, 0:22)	0:26 (0:23, 0:30)	7.8 (3.6, 11.9)	0.96
	Continuously low	0:25 (0:16, 0:34)	0:35 (0:26, 0:44)	10.2 (1.2, 19.8)	
	Increase	0:18 (0:12, 0:24)	0:26 (0:17, 0:35)	7.8 (1.2, 15.0)	
	Continuously high	0:13 (0:09, 0:17)	0:22 (0:17, 0:26)	9.0 (3.0, 13.8)	
	Decrease	0:17 (0:10, 0:25)	0:24 (0:17, 0:31)	6.0 (−3.0, 16.2)	

Adjusted for gender, age, occupation, accelerometer wear time (except for transportation PA), measurement season, and residential area population density. PA = physical activity, MVPA = moderate-to-vigorous physical activity.

in contrast to previous studies utilizing residential greenness (Li et al., 2008; Mytton et al., 2012; Puhakka et al., 2020; Villeneuve et al., 2018) or activity space greenness (Boakye et al., 2021; James et al., 2017; Marquet et al., 2022; Tamura et al., 2019) and PA measured with either questionnaires or accelerometers. However, none of the previous studies reported transportation PA specifically. Although our study sample consisted mostly of women, the gender distribution does not seem likely to explain the differences as the samples in the previous activity space greenness utilizing studies were women only (James et al., 2017; Marquet et al., 2022) or 53 % women at lowest (Tamura et al., 2019). Three of the five previous studies that found a positive association between activity space greenness and PA used a momentary approach – i.e., higher exposure to greenness associated with more PA within the same minute (Boakye et al., 2021; James et al., 2017; Tamura et al., 2019). However, in one study higher momentary exposure to greenness associated with lower step count (Wilt et al., 2023), which may be related to the sample consisting entirely of nurses. Moreover, employment was not systematically controlled for in the previous studies.

Previously, a Finnish study of over 5000 working age adults observed a negative association between residential greenness and MVPA in women which is in line with our negative association between exposure to greenness and MVPA on workdays (Puhakka et al., 2020). Additionally, they found that higher residential greenness was associated with more accelerometer-measured light PA in men but not in women after adjusting for health status, socioeconomic factors, and sports facilities (Puhakka et al., 2020). In our study, higher exposure to greenness within the GPS-based activity space on workdays was associated with higher light PA in women only. The participants were older in our study (63 vs. 46 years) and the method for greenness exposure assessment was different (residential vs. GPS-based activity space greenness), which could explain the different gender-stratified results between the studies. However, a recent study using similar GPS-based activity space exposure to greenness (albeit without time-weighting) did not find an association between activity space NDVI and PA of any intensity among 31 younger adults 61 % of whom were men (Vittor et al., 2025). However, higher NDVI within a minimum convex hull activity space (which is a broader area compared to the buffered track method) associated with more light PA (Vittor et al., 2025).

In the occupation-stratified cross-sectional analysis, we observed that higher exposure to greenness on days off associated with more light

PA among non-manual workers. Speculatively, this could mean that individuals with higher socioeconomic status (i.e., non-manual occupation) participate more often in light activities in green environments, such as gardening or lightly walking in a park.

4.2. Longitudinal findings

In contrast to the cross-sectional results, we did not observe any associations between the changes in exposure to greenness and PA behavior, which suggests that individuals may change their PA behavior irrespective of how much they spend time in green areas. However, without any qualitative methods, such as interviews or self-reports (e.g., soft GIS), it is not possible to investigate the individual preferences for green spaces and meanings for PA in certain environments (Bell et al., 2015). Previous longitudinal evidence remains limited, but it suggests that increasing residential area greenness (either by moving or changes in the environment) could be associated with decreasing PA (Persson et al., 2019; Van Beek et al., 2024) or a greater likelihood of reducing the number of behavior-related risk factors (Kivimäki et al., 2021). It should be noted that these previous studies used questionnaires for PA assessment, which are prone to recall and response biases (Prince et al., 2008), as opposed to the accelerometers we used. Moreover, participants in these previous studies were younger (44–55 years old at baseline) (Persson et al., 2019; Van Beek et al., 2024) than our participants (62 years old at baseline). Finally, in line with our finding that changes in exposure to greenness were not associated with the changes in PA, a recent analysis using GPS and accelerometer data observed that women participating in a weight loss trial did not increase PA in green environments (Luo et al., 2025). Our findings that higher exposure to greenness on workdays associated with lower moderate-to-vigorous and transportation PA cross-sectionally, but not longitudinally suggests that work-related constraints (e.g., commuting, workplace location, or work-related physical demands) play a role in the association between exposure to greenness and PA. It is therefore important that future studies consider working status as a confounding factor.

Interestingly, our longitudinal analyses suggest that the individuals with the continuously low exposure to greenness spend the highest time in transportation PA, regardless of the day type. When the analysis was conducted among only participants living in an urban area, the difference turned statistically non-significant (p = 0.14), and a similar result

was obtained when the main analysis was adjusted for residential area NDVI. These results likely reflect the poorer possibilities for physically active transportation in rural areas, where distances to work or leisure facilities may be longer than in urban areas. However, even though the difference was not significant among urban-living participants, the high exposure group still tended to have the least transportation PA. This could imply that greener areas even within the urban or suburban areas might have higher destination distances or poorer street connectivity. A study from Canada using survey data also observed that higher activity space greenness was associated with less transportation PA (Van Heeswijck et al., 2015). Moreover, results from the US and Canada also show that rural-living individuals are less physically active, especially in transportation PA (Abildso et al., 2023; Pelletier et al., 2023). In a way, the finding that the exposure to greener and more rural areas associates with less transportation PA supports the main finding that individuals would be physically active or inactive regardless of exposure to greenness, and there are other factors, such as walkability, which also affect PA (Marquet et al., 2022). Finally, the observation that moving to a greener area associates with decreased walking and cycling (which would be mostly transportation PA) (Persson et al., 2019) further support the hypothesis that higher greenness, at least when distances and walkability are not accounted for, could in fact associate with less transportation PA. Future studies should also address walkability in addition to greenness, as accessibility of greenspace is important especially among older adults (i.e., >65 years old) (Miralles-Guasch et al., 2019).

4.3. Strengths and limitations

First, a major strength in this study is the measurement of exposure to greenness. Studies utilizing device-based measures of activity space greenness and PA are still relatively few. Unlike the prior studies that rely on either residential area greenness or activity space greenness without time-weighting (Marquet et al., 2022; Puhakka et al., 2020), we were able to utilize high-resolution spatiotemporal measurements of how long and where each participant was during the measurement period. Furthermore, NDVI is a widely used index in epidemiological studies for estimating exposure to greenness in both urban and rural areas (Rheew et al., 2011). However, even this approach comes with limitations that should be acknowledged. For instance, by using only GPS-based location, it is not possible to distinguish whether the individual is indoors or outdoors. Consequently, an individual may gain notable exposure to greenness even by staying indoors if the building is located in a green area. For example, mean exposure to greenness was higher in participants living in rural compared to urban areas on all day types (0.53 vs. 0.45 NDVI units, $p < 0.0001$, on average), and rural-living participants spent more time at home (7 h 42 min vs. 6 h 39 min/day, $p = 0.005$, on average), which shows that living in a green area affects the exposure. Yet, the main results remained unchanged when residential rurality or NDVI was adjusted for. Also, any overlapping exposure during periods of inactivity was handled implicitly through temporal weighting and inverse-distance interpolation, allowing cumulative exposure to be estimated without artificial inflation.

Additionally, while NDVI is an objective measure of greenness, it does not consider the usability or type of the environment. Previous evidence shows that different natural environments associate with different PA types and the size of the natural environment associates with MVPA volume (Jansen et al., 2017). For example, a public park is a more likely venue for PA than a private garden – both of which would count towards measured exposure to greenness regardless of accessibility. However, the NDVI we measured represents the environment that the participants actually visited (i.e., the activity space), and therefore we can assume that all measured exposure to greenness could potentially impact PA behavior. The buffer around each GPS point was 150 m, and an individual could in many situations perceive and interact with the environment within this buffer (Laatikainen et al., 2018; Raudsepp

et al., 2025). Yet, it should be acknowledged that the time-weighted exposure was quantified as mean NDVI within the activity space. Consequently, two individuals could end up with the same estimated exposure if one spent the whole day in a mid-green area and one spent half of the day in a non-green and half of the day in a highly green area. Furthermore, in this study, the NDVI data represent a two-year temporal average (2018–2019) and cover only a part of the overall study period (2015–2022).

Second, we used accelerometers to quantify PA intensity and duration. An accelerometer-based estimate of PA can be considered less biased compared to self-reports, which are prone to either over- or underestimation depending on the method used (Prince et al., 2008). A limitation of accelerometers is the lack of context for the detected PA; however, we used diaries to distinguish workdays and days off. Another limitation of accelerometers is the inability to measure strength training type exercises or isometric muscle work, but in the context of this study, it is reasonable to assume that exposure to greenness would mostly be related to outdoor activities that are performed in green environments, such as walking or jogging. Nevertheless, even the accelerometer measurement itself can affect PA, as the measured participants may modify their behavior during the measurement, even if the participants were instructed to maintain usual PA behaviors during the measurement. The repeated measure setting in this study could potentially reduce bias related to individual differences, as the same individuals were measured before and after retirement, and one could expect similar behavior during the measurement within an individual. Furthermore, the GEE analysis takes the intraindividual correlation of the repeated measures into account statistically.

The sample size is an important limitation of this study. Although most of the greenness change groups had >30 participants each, the smallest group (decrease in exposure to greenness) had only 18 participants, which markedly reduces the statistical power for detecting potential associations. Moreover, the sample size limits the possibilities to perform further subgroup or sensitivity analyses.

Weather is known to affect PA (Albrecht et al., 2020), but we were not able to adjust for it in this study. However, we did adjust all models for the measurement season, and the measurements were performed on the same season for each participant before and after retirement. Moreover, we had a relatively even distribution of all seasons in our measurements. Therefore, with the sample size of 123, it is unlikely that the individual weather conditions notably affected our results.

While transition to statutory retirement provides a unique natural experiment setting that is useful for studying the associations between changes in exposure to greenness and PA behavior, its limitations should be acknowledged. Importantly, transition to retirement may introduce noise that can mask the associations between greenness and PA. For example, increased burden of giving informal care, reduced financial possibilities, or changes in social relationships may also shape PA behavior.

The IREM model has primarily been used to analyze PPGIS data, which rely on mapped point locations such as home and visit location along with the frequency of visits but no measured information of the travelled routes. The exposure model used in this study was developed to support the GPS dataset sharing the common operational concepts. Finally, the study participants lived in the Southwest Finland region and the study area was restricted to cover 75 km outside this region. This approach likely ensured that most routine travel behavior was included in the data, but it is not possible to distinguish routine and incidental travel with only measured data.

5. Conclusion

We found that higher exposure to greenness was associated with less MVPA and transportation PA on workdays. However, changes in exposure to greenness were not associated with changes in PA behavior before and after retirement. Further studies with larger sample sizes are

needed to investigate whether the findings are generalizable to other age groups, genders and geographical settings.

Declarations of competing interest

The authors have no competing financial interests or personal relationships to declare.

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CRediT authorship contribution statement

Jooa Norha: Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Arpa Aishwarya:** Formal analysis, Investigation, Writing – review & editing. **Carlos Gonzales-Inca:** Formal analysis, Investigation, Supervision, Writing – review & editing. **Kamyar Hasanzadeh:** Investigation, Supervision, Writing – review & editing. **Sanna Pasanen:** Conceptualization, Writing – review & editing. **Jaana Pentti:** Data curation, Formal analysis, Investigation, Writing – review & editing. **Jussi Vahtera:** Conceptualization, Investigation, Supervision, Writing – review & editing. **Nora Fagerholm:** Investigation, Supervision, Writing – review & editing. **Sari Stenholm:** Conceptualization, Formal analysis, Investigation, Supervision, Writing – review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.healthplace.2026.103653>.

Data availability

Data will be made available on request.

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