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Green commutes: Assessing the associations between green space exposure along GPS-track commuting routes and adults' self-perceived stress

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ABSTRACT

Background: Habitual commutes through green space may be associated with health promotion, including stress alleviation. However, few studies have assessed green space exposure during commuting with stress levels, and none have tracked commuters' actual routes.

Aim: To assess 1) the association between commuting through green space and people's self-perceived stress, 2) whether the association is moderated by the transport mode, and 3) whether the association depends on differing green space operationalizations and buffer sizes.

Methods: This cross-sectional study used questionnaires and global positioning system data from Dutch adults aged 18–65 ($N = 275$). The Perceived Stress Scale was used to measure people's stress levels. Green space was measured by calculating the green space percentage from land use data ($GREEN_{LU}$), and by using normalized difference vegetation index (NDVI) obtained from Sentinel-2 ($NDVI_{SE}$) and Landsat-8 ($NDVI_{LS}$) satellite imagery. Buffers of 50, 100, and 250 m along commuting routes were applied to assess subjects' environmental exposures. Associations were estimated using ordinary least squares regression models.

Results: Covariate-adjusted regressions showed that $GREEN_{LU}$ was significantly but positively associated with stress levels, regardless of the buffer size. By contrast, the NDVI measures consistently showed null associations. We observed a positive association between $GREEN_{LU}$ and stress levels among active commuters within the 250 m buffer in stratified analyses; however, associations were null for passive commuters across all green space measures and buffer sizes.

Conclusions: Our findings suggest a counterintuitive positive association between increased exposure to green space during daily commutes and people's stress levels. These associations possibly may depend on the selected green space metric, the buffer sizes, and the commuting mode considered. The behavioral aspects of how people experience green environments, including commuting, may contribute to their impact on health.

1. Introduction

Commuting represents a substantial component of employees' daily travel (Tao et al., 2023), with both travel distance and duration increasing (Savills, 2021). There is mounting evidence that commuting may influence mental health and well-being (Chatterjee et al., 2020; Ettema et al., 2016; Garling, 2019). While the transport literature primarily focuses on commuting mode, trip duration, and travel circumstances (e.g., crowding) (Liu et al., 2022), only a few studies have assessed to what extent the physical environment encountered during travel is associated with mental health outcomes (Khreis et al., 2016; Poom et al., 2021; Zijlema et al., 2018). Environmental factors such as exposure to green space (e.g., parks and street trees) have been acknowledged for their allegedly positive mental health effects, including stress relief and support for mental restoration (Hartig et al., 2014; Markevych et al., 2017; Wang et al., 2021; Yañez et al., 2023).

Most previous studies evaluating green space-health associations have focused on assessing green space solely at residential locations (Labib et al., 2020). Such residence-based green space assessments are conceptually insufficient, as articulated by the uncertain geographic context problem (Kwan, 2012), as commuters' day-to-day environmental exposures en route are disregarded (Helbich, 2018; Song et al., 2018). Therefore, mobility-based exposure associations may differ from residence-based ones (Campbell et al., 2021).

Acknowledging the presumed health benefits of green spaces, incorporation of exposure to green spaces into peoples' commuting

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routines might be a strategy for enhancing mental health. Previous studies generally used self-reports (Zijlema et al., 2018) or computed the shortest path between the home and work location (Higuera-Mendieta et al., 2021); neither approach captures the actual commuting route, which may deviate considerably in terms such as route lengths and exposure levels. Global positioning system (GPS) enabled devices such as smartphones allow tracking of people's day-to-day mobility precisely in space-time (Birenboim et al., 2021; Faka et al., 2021). The current ubiquity of smartphones now allows their use to alleviate recall bias (Zijlema et al., 2018). Additionally, travel-specific information, such as route and mode choice, can be inferred (Wei et al., 2023a). Nonetheless, only limited studies have examined how green space during travel is associated with commuters' mental health, with even fewer using GPS-tracking.

To the best of our knowledge, only one study has investigated the association between mental health and green space exposure during commuting (Zijlema et al., 2018). The authors reported that active commuting was associated with better mental health, but only when participants reported commuting through natural environments. However, the study relied on self-reported green space exposure assessments during travel, which are susceptible to recall biases and unable to depict actual commuting routes and objective green space exposures (Fadnes et al., 2009). Furthermore, Zijlema et al. (2018) did not investigate whether the green space-mental health association may vary across commute modes. It is conceivable that active and passive modes result in distinct commuting experiences, resulting in divergent physiological responses (van Wee & Ettema, 2016).

Two other concerns with previous environmental health studies are the choice of the buffer size to delineate the geographic context and the exposure metric (Brownson et al., 2009; Sarjala, 2019; Wong et al., 2011; Wu & Kim, 2021). A review identified inconsistencies in the application of buffer sizes across studies, contributing to uncertainties in the estimated associations with green spaces (Labib et al., 2020). Furthermore, speculation exists regarding the input data used to determine the green space exposure metric. For example, some studies used land use data to define green space (Houlden et al., 2017), while others used the normalized difference vegetation index (NDVI) derived from satellite imagery (Spano et al., 2023; Zhang et al., 2022). Comparative case studies that systematically assess to what extent different buffer sizes result in varying effect sizes remain inconclusive and only focus on assessments based on residence (Helbich et al., 2021). Our best understanding is that no study has yet addressed how commuting route-based buffer sizes and differing green space operationalizations translate into green space-mental health associations.

Addressing these research gaps, the current study employed GPS tracking data from the Netherlands. We aimed to 1) assess the associations between green space exposure along the commuting route and adults' self-perceived stress, 2) discover whether the associations were moderated by commuting mode (active vs. passive commuting), and 3) find to what extent different green space operationalizations and buffer sizes influenced the estimated associations.

2. Materials and methods

2.1. Study design and participants

Our study relied on Dutch cross-sectional survey and tracking data (Helbich, 2019). Stratified random sampling identified 45,000 potential participants aged 18–65, living in a private household, and who had not been sampled by Statistics Netherlands in the previous year. Between September and November 2018, an online questionnaire addressed participants' mental health, socio-demographics, and living environments that 11,505 participants completed (25.6 % response rate). Of these participants, 8869 consented to be recontacted. Follow up invitation letters and instructions were sent out within two days after survey completion. This invitation resulted in 799 respondents downloading our 'Your Living Environment' GPS tracking application (version 4.4+).

We configured the application to operate in the background on installed devices to minimize interference with participants' daily activities and behaviors. The app recorded seven days of data using adaptive sampling to ensure sustainable battery use (Lan et al., 2022). Every 20 s, the app probed respondents' locations. If the smartphone showed less than 20 m displacement for more than 30 min, the recording interval fell-back to polling every 60 s. The app reduced location sampling frequency to every two minutes when it detected no significant movement within an hour. The Ethics Review Board of Utrecht University approved the study (FETC17-060).

2.2. GPS data

2.2.1. Preprocessing

Owing to signal inaccuracies resulting in spatially fluctuating locational information, before use, GPS data must undergo data cleaning (Yuan & Li, 2021). We applied five preprocessing steps to ensure the quality and reliability of our data and resulting analyses. First, since our focus was on commuters, we filtered out respondents who were unemployed and excluded those with missing questionnaire data. Second, people with GPS records indicating they were outside the country were removed, as likely not representing a typical week of commuting. Third, we removed people tracked less than two days. Fourth, implausible GPS records (e.g., a speed of >200 km/h) (Bohte & Maat, 2009) and located >50 m apart from the transportation network were also removed (Wei et al., 2023a). Fifth, we removed respondents without traceable commuting routes due to a paucity of relevant GPS records. Fig. 1 summarizes the data-cleaning procedure.

2.2.2. Extraction of the home and workplace

Due to a lack of available data on respondents' workplace locations, we estimated the home and workplace locations using the GPS records. Following previous practice (Chen et al., 2014; Wei et al., 2023b), we

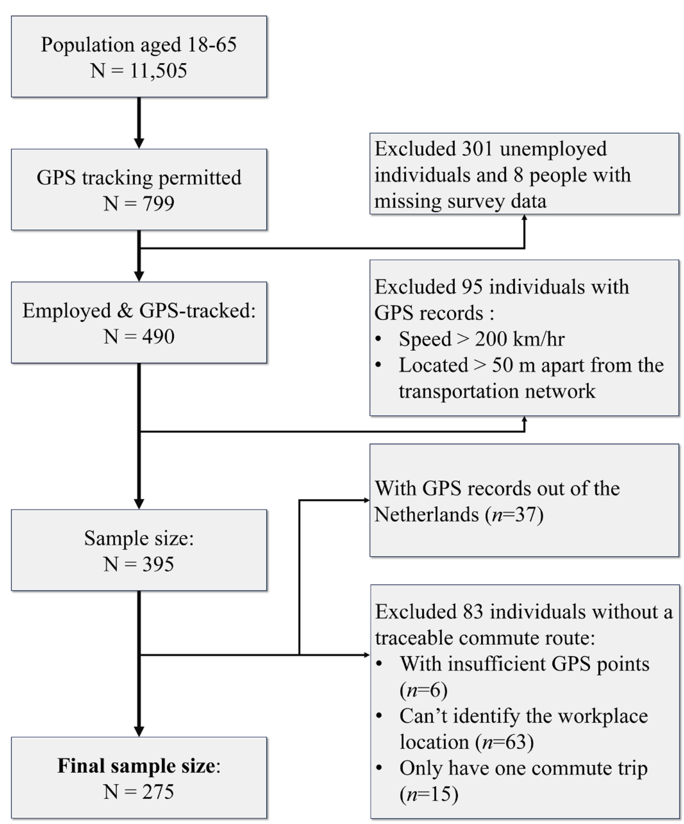

Fig. 1. Flow chart of participant selection for inclusion in the analysis.

assumed that employees spend most of their day at their residential locations, followed by their workplace. Accordingly, we clustered GPS points based on dwell time, where the cluster with the longest dwell time represented the home while the cluster with the second longest dwell time indicated the workplace. We also assumed that the home-work commute encompassed at least two separate trips. Based on these assumptions, we matched trips to the road network for 2018 obtained from OpenStreetMap using the Leuven. Map Matching (Meert & Verbeke, 2018) and OSMnx (Boeing, 2017) Python (version 3.9.7) packages.

2.2.3. Detection of the transport mode detection

We determined the commute mode of each trip by applying a rule-based approach based on travel speed (Wei et al., 2023a). Due to the unavailability of pre-labeled training data to classify specific travel modes (e.g., tram and bus), we categorized commute modes for each trip into either active (i.e., walking and cycling) or passive modes (i.e., car and public transport). Trips made actively were assumed to have an average speed of <25 km/h and a maximum speed of <45 km/h. Passive trips had an average speed of <200 km/h (Shafique & Hato, 2016; Wei et al., 2023a). As respondents undertook multiple trips, we aggregated commute modes at the personal level to align with participants' mental health data. A respondent was characterized as an active mode user if all the user's trips were active. Similarly, passive mode users represented those whose trips were passive, and users of multiple commute modes were multiple-mode users.

2.3. Measures

2.3.1. Perceived stress as outcome

Participants' stress was measured using the Perceived Stress Scale (PSS) (Cohen et al., 1983). The instrument has ten self-reported items related to respondents' stress levels over the previous month. Likert scales ranging from 0 ('never') to 4 ('very often') represented each item. Six items had negative wording (e.g., '…how often have you felt nervous and stressed?') to capture uncontrollable and perceived distress. Four had positive wording (e.g., '…how often have you been able to control irritations in your life?') to obtain people's capacity to cope with stress. After reverse scoring four positively worded items, we summed the item scores to receive a total stress score ranging between 0 ('no perceived stress') and 40 ('high perceived stress'). The items showed strong internal consistency (Cronbach's alpha = 0.89).

2.3.2. Green space mapping

Green space can be mapped through different metrics derived from various satellite imagery with diverse spatial resolutions (Helbich et al., 2021; Labib et al., 2020). Due to a lack of agreement on the most applicable metric, we used three green space indicators. First, we used the NDVI. This index represents vegetation greenness based on surface spectral reflectance (Tucker, 1979). With values ranging between −1 and +1, higher positive NDVI values represent more greenness. We relied on two datasets from Google Earth Engine (Gorelick et al., 2017) to derive the NDVI using Sentinel-2 satellite images ($NDVI_{SE}$) with a 10 m resolution and Landsat-8 images ($NDVI_{LS}$) with a 30 m resolution. We collected satellite imagery from May through September 2018, temporally aligned with our other data. To prevent distortions in the NDVI measure, we masked pixels, typically representing non-biomass areas, with negative values.

Second, we acquired land use data for 2018 ($GREEN_{LU}$) (Hazeu et al., 2020). This high-resolution dataset with a 5 m resolution distinguishes 48 land use categories. We merged 33 categories (e.g., natural and agricultural areas as well as human-made green spaces such as parks; see Appendix Table A.1) using a geographical information system to obtain a single binary green space measure (Bloemsma et al., 2022; Klompmaker et al., 2019).

2.3.3. Green space exposure assignment

We assigned each participant's exposure to green space along their commuting routes, including at their home and workplace. The three green space metrics were each assessed with 50 m, 100 m, and 250 m commuting route-based buffers. The chosen buffers reflected adjacent green space proximity and visibility (Badland et al., 2010; Sarjala, 2019). Each NDVI measure had average pixel values per buffer determined. In the land use-based case, we computed the proportion of pixels classified as green space.

2.4. Covariates

We included several personal- and household-level covariates per practice elsewhere (Collins et al., 2020; Roberts & Helbich, 2021). Included were age (in years), sex (male/female), nationality (Dutch, non-Dutch), education (low [no education or primary school], medium [up to higher secondary school], and high [university or higher]). At the household level, we included household structure (couple with child (ren), couple without child(ren), single parent, and others) and income quintiles (1=lowest, 5=highest). Due to our limited sample size, we treated income as continuous. As trip-specific covariates, we adjusted for logged commute distance (in km) and commute mode (active, passive, multiple-mode) (Chatterjee et al., 2020; Liu et al., 2022).

We also included four measures of the built environment. Using the address and building register for 2018 (Kadaster, 2018), address density was operationalized based on the number of residential addresses per km^2. The land-use mix was derived from Dutch land use data (i.e., Bestand Bodemgebruik) for 2017 (CBS, 2019) by computing the Shannon entropy index based on five land use types grouped into residential, recreational, commercial, industrial, and others (Liu et al., 2023). We measured street connectivity by intersection count (three-way or more) per km^2 extracted from the topographic map of the Netherlands in 2018. Street connectivity and address density were log-transformed to achieve a less skewed distribution.

Given substantial correlations between address density and street connectivity (e.g., a Spearman's correlation coefficient of 0.89 for the 50 m buffers), we employed principal component analysis (PCA) with varimax rotation to acquire a small set of orthogonal principal components reflecting most data inherent information (Maćkiewicz & Ratajczak, 1993). We performed principal component analysis independently for each buffer size using the "FactoMineR" R package (Lê et al., 2008). Two principal components were deemed suitable and jointly explained

Table 1
PCA loadings.

Buffer size		1st principal component Density	2nd principal component Diversity
50 m	Address density	0.92	
	Street connectivity	0.91	
	Land-use mix		0.99
	Explained variance	56.81 %	33.34 %
100 m	Address density	0.93	
	Street connectivity	0.93	
	Land-use mix		0.99
	Explained variance	58.05 %	33.16 %
250 m	Address density	0.93	
	Street connectivity	0.94	
	Land-use mix		0.98
	Explained variance	59.26 %	32.80 %

Note: Only loadings >0.3 are shown.

approximately 90 % of the variance (Table 1). The first principal component included address density and street connectivity, while the second captured land-use diversity.

2.5. Statistical analyses

2.5.1. Main analyses

We summarized the data using descriptive statistics (i.e., mean, standard deviation [SD], and percentage-based [%]). The Wilcoxon test was applied to examine the difference in perceived stress between the retained and raw samples. Spearman correlations assessed pairwise bivariate associations between the environmental exposures. Finally, we examined green space exposure differences between buffer sizes using the ANOVA and used generalized variance inflation factors (GVIF) to test for covariate multicollinearity; GVIF values >10 were deemed critical (Mohammad et al., 1999).

The PSS score representing participants' average stress levels over the previous month was measured only once; however, participants generally made multiple trips during the tracking period. Hence, we averaged participants' trip-level exposures at the individual level (Foster-Johnson & Kromrey, 2018), averaging also supported by minor variations by minor exposure variations across trips (Fig. A.1). We fitted ordinary least squares (OLS) regressions to estimate the associations between commuting route-based green space exposure and commuters' PSS scores. Following, we applied the White-Davidson-MacKinnon correction to account for heteroscedasticity across group sizes (i.e., the number of tracked commute trips per individual). Each green space measure had an individually developed regression model (applied to the 50, 100, and 250 m buffers). Model 1 included green space and sociodemographic characteristics. Model 2 added built environmental variables, logged commute distance, and commute mode based on Model 1. Moreover, we stratified the sample to assess whether the green space-stress associations varied across active (Model 3) and passive transport modes (Model 4). Analyses used R, version 4.3.0 (R Core Team, 2023).

2.5.2. Sensitivity analysis

We conducted sensitivity tests to evaluate the results' robustness. Considering that exposure duration may influence commuters' green space experience, it seems plausible that prolonged green space exposures may exert more significant effects on health than short-term exposures (Jankowska et al., 2023). Thus, we calculated a commute duration weighted average exposure for each participant and then used these time-weighted exposures to construct Model 5.

3. Results

3.1. Sample characteristics

The Wilcoxon test indicated no significant difference in the PSS scores between the whole and the analytic samples ($p = 0.52$). We had 275 respondents who made between 2 and 21 trips each, averaging 5.89 per respondent (Table A.2). The mean PSS score was 11.28 (SD ± 6.28). Our respondents had a mean age of 45.81 (SD ± 12.15), and 58.18 % were males. Approximately 70.18 % commuted via a single mode (i.e., active or passive), with most opting for passive commuting. Sentinel-based NDVI scores were, on average, higher than the Landsat-based NDVI scores. Green space exposure increased with increasing buffer sizes, regardless of the data utilized.

3.2. Bivariate analysis

The correlations between the green space metrics across buffer sizes are shown in Figure A.2. $NDVI_{SE}$ and $NDVI_{LS}$ were strongly correlated (0.92–0.99) across all buffer sizes. Correlations between the NDVI indices and $GREEN_{LU}$ were slightly lower, with the highest being 0.87. We also observed a minor increase of 8 % [SD ± 3 %] in the correlation magnitude as buffer sizes increased. $GREEN_{LU}$'s correlation with $NDVI_{LS}$ was stronger than with $NDVI_{SE}$. The ANOVA results indicated statistically significant differences between the three vegetation indices across different buffer sizes (Table A.3).

3.3. Regression results

Multicollinearity among covariates was not evident (GVIF values <10) (Table A.4). Table 2 shows the covariate-adjusted associations between different green space metrics and PSS scores across different buffers (see Appendix Table A.5 for detailed results). Green space indices, dependent on buffer size, showed differences in their associations with the PSS scores. $GREEN_{LU}$ was positively associated with stress across all buffer sizes. However, NDVI-based metrics showed null associations with the PSS scores across all buffer sizes.

3.4. Stratified analysis by active and passive mode

Table 3 summarizes the regression results stratified by commute modes (see Appendix Table A.6–7 for detailed results). The results indicated that the associations between the PSS scores and green space exposure during commute differ across commute modes. $GREEN_{LU}$ was positively associated with stress among active commuters at 250 m buffers, while it was insignificantly associated using 50 m and 100 m buffers. Associations between NDVI-based metrics and the PSS scores were null. For the passive commuters, we observed null associations across all green space measures and buffer sizes.

3.5. Sensitivity analysis

Our primary findings were replicated in our sensitivity analysis. Including commute duration-weighted exposures at various buffer sizes demonstrated consistent stress-green space associations as obtained in Model 5 (Table A.8). For the commute mode stratified analyses, the results again were aligned with our primary findings (Table A.9–10).

4. Discussion

4.1. Principal findings

We aimed to assess associations between adults' green space exposure along their commuting routes and their stress levels. Our study went beyond preceding scholarship by measuring commuting-related green space exposure using GPS tracking rather than self-reports in prior analyses (Zijlema et al., 2018). The results showed that land-use-based green space measures showed a consistent positive association with stress levels across buffer sizes. We observed null associations for NDVI, regardless of whether green space was determined from high- (i.e., Sentinel-2) or moderate-resolution imagery (i.e., Landsat-8). Moreover, the commuting route-based green space-stress associations differed between active and passive transport modes. Active commuters' stress levels were significantly positively associated with land-use-based green space assessed at 250 m buffers, while we observed null associations among passive commuters across all green space measures and buffer sizes.

4.2. Interpretation of the findings

As the first study employing GPS-tracked routes to investigate the association between exposure to green space during commuting and stress, we discuss our findings in the context of residential green space and mobility-based studies which incorporated travel-based exposures for other than commuting purposes. Previous studies, predominantly residential-based and daily mobility path-based, have found mental health benefits associated with green space (Callaghan et al., 2021;

Table 2
Fully adjusted OLS models for different green space measures across various buffers with White-Davidson-MacKinnon correction applied to the number of trips per person.

		$GREEN_{LU}$		$NDVI_{SE}$		$NDVI_{LS}$	
Buffer		Coef. (95 % CI)	*p*-val.	Coef. (95 % CI)	*p*-val.	Coef. (95 % CI)	*p*-val.
50 m	**Green space**	10.226 (9.551, 10.902)	0.046*	8.343(7.664, 9.022)	0.146	11.295(10.617, 11.973)	0.124
	Adjusted R-squared	**0.1271**		**0.1198**		**0.1213**	
	AIC	**1764.573**		**1767.071**		**1766.557**	
100 m	**Green space**	12.699 (12.023, 13.376)	0.037*	8.042 (7.361, 8.723)	0.176	10.777 (10.097, 11.458)	0.157
	Adjusted R-squared	**0.1242**		**0.1136**		**0.1147**	
	AIC	**1765.592**		**1769.188**		**1768.817**	
250 m	**Green space**	18.587 (17.909, 19.266)	0.012*	11.206 (10.523, 11.890)	0.085	13.701 (13.018, 14.385)	0.086
	Adjusted R-squared	**0.1204**		**0.1069**		**0.1066**	
	AIC	**1766.865**		**1771.490**		**1771.564**	

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models were adjusted for gender, age, nationality, income quintile, education levels, household composition, commute mode, logged commute distance, and two principal components of the built environment (i.e., density and diversity).

Table 3
The fully adjusted OLS model for active and passive commuters.

		Active commuters ($N = 153$)			Passive commuters ($N = 187$)		
Buffer		Coef. (95 % CI)	*p*-val.	Adjusted R-squared (AIC)	Coef. (95 % CI)	*p*-val.	Adjusted R-squared (AIC)
50 m	$\mathbf{GREEN_{LU}}$	14.480 (13.512, 15.447)	0.080	**0.1125 (1009.802)**	2.644 (1.828, 3.459)	0.720	**0.0912 (1203.572)**
	$\mathbf{NDVI_{SE}}$	9.557(8.582, 10.531)	0.224	**0.0983 (1012.599)**	2.310(1.494, 3.125)	0.750	**0.0908 (1203.654)**
	$\mathbf{NDVI_{LS}}$	15.580(14.610, 16.551)	0.118	**0.1059 (1011.109)**	0.764(−0.052, 1.579)	0.934	**0.0904 (1203.744)**
100 m	$\mathbf{GREEN_{LU}}$	16.889 (15.921, 17.857)	0.050	**0.1106 (1010.168)**	4.276 (3.457, 5.095)	0.659	**0.0838 (1205.263)**
	$\mathbf{NDVI_{SE}}$	9.633 (8.654, 10.613)	0.222	**0.0903 (1014.156)**	1.661 (0.841, 2.480)	0.828	**0.0826 (1205.550)**
	$\mathbf{NDVI_{LS}}$	16.103 (15.129, 17.078)	0.111	**0.0985 (1012.558)**	−0.176 (−0.996, 0.643)	0.986	**0.0824 (1,205.594)**
250 m	$\mathbf{GREEN_{LU}}$	21.382 (20.412, 22.351)	0.028*	**0.1081 (1010.671)**	12.532 (11.714, 13.350)	0.288	**0.0863 (1204.706)**
	$\mathbf{NDVI_{SE}}$	13.579 (12.598, 14.560)	0.109	**0.0877 (1014.662)**	5.752 (4.931, 6.572)	0.479	**0.0800 (1,206.143)**
	$\mathbf{NDVI_{LS}}$	20.318 (19.342, 21.295)	0.054	**0.0953 (1013.181)**	4.635 (3.814, 5.456)	0.637	**0.0788 (1206.422)**

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. The models were adjusted for gender, age, nationality, income quintile, education levels, household composition, logged commute distance, and two principal components of the built environment (i.e., density and diversity).

Markevych et al., 2017; Zhu et al., 2023). For example, a Dutch study reported that residential green space was inversely associated with psychological distress (Klompmaker et al., 2019), and green space along daily mobility paths was associated with reduced depressive symptoms (Roberts & Helbich, 2021) and momentary stress (Yu & Kwan, 2024). However, we observed an unexpected negative association between green space and stress in the commuting context.

The divergent associations may stem from our nuanced emphasis on green space during commuting, an activity that precludes other interactions (e.g., social activities) with such green space beyond visual recognition. Geographic context varies between participants' residential locations and commuting spaces. Such contextual variance generates specific combinations of movement, time, and environmental attributes, resulting in differing behaviors and perceptions (Jankowska et al., 2023; Rainham et al., 2010). This diversity, in turn, leads to differences in the health implications associated with green space exposure (Kim et al., 2023). Furthermore, compared to a well-maintained neighborhood environment, green space along commute routes perceived as 'wild' may trigger innate sources of fear and anxiety (Koole & Van den Berg, 2004). Regarding the daily mobility path-based approach, these studies cover daily trips for all purposes (Lan et al., 2022; Roberts & Helbich, 2021; Yu & Kwan, 2024), such as grocery shopping and leisure activities, whereas our research solely includes trips for the purpose of commuting. It is plausible that including or excluding trips other than commuting may yield different mental health effects from traversing green space. In addition, we hypothesize that the mental health benefits of green space during non-commuting activities may partially offset the negative effects experienced during commuting trips. Nevertheless, further research is needed to substantiate this hypothesis.

Direct comparisons with Zijlema et al. (2018), the sole other study on green commuting, are impossible due to differences in their research designs. Their cross-sectional study found health-supportive associations between active commuting through green space and mental health among adults across four European cities. The inconsistency may be partially due to how green space was measured. We objectively measured green space exposures en route using three different measures. By contrast, Zijlema et al. (2018) acquired green space information based on participants' self-reports. However, such subjective evaluations may lead individuals to report satisfaction with their exposures, even in cases where access to green spaces is limited (Orstad et al., 2017). Subjective experiences may encompass other perceived qualities of green spaces, potentially playing an even more significant role in mental health benefits than quantitative measures (Ettema & Schekkerman, 2016; Zhang et al., 2021). Second, in Zijlema et al. (2018), four countries provided samples (i.e., Spain, Lithuania, the United Kingdom, and the Netherlands), while we focused solely on the Netherlands. The differences in urban structure, population characteristics, and green space infrastructure across our study areas could also contribute to the differing associations. Another factor possibly explaining the observed heterogeneity across studies is the definition of commuting. Zijlema et al. (2018) included travel for other daily activities (e.g., recreational walking or walking with the dog), while ours was more tightly focused only on the home-work trip and vice versa. The transport literature has established that, compared to other travel purposes, commuting tends to be more psychologically demanding (Holland, 2016; Zhu & Fan, 2018). While we observed a positive green space-stress association only for active commuters, it could be that such commuters establish a more direct connection with the surrounding green space, encompassing visual, auditory, and olfactory stimuli, compared to passive commuters who are comparatively more isolated from the environment. In addition, passive commuters might be drawn to social media utilities due to a fear of missing out on social or work-related interactions (Przybylski et al., 2013; Stavrinos et al., 2018), resulting in limited interactions with green space during their commute. Consequently, active commuters may more strongly experience positive as well as negative effects (Apparicio et al., 2018; Willberg et al., 2023).

We emphasize that our results are not an outlier; other studies have also reported null or counterintuitive associations (Gatersleben & Andrews, 2013; Picavet et al., 2016; Trammell & Aguilar, 2021). In the context of commuting, the positive association observed in our analysis might be elucidated by the heightened sensitivity to green space during commuting time, possibly due to safety concerns (Sreetheran & Van Den Bosch, 2014). Especially in the early morning or late evening, a higher density of green space could amplify the perception of "fear of crime" (Ceccato et al., 2020; Lorenc et al., 2012). Notably, our data collection was between September and November, when the dawn is much later than in summer. Moreover, commuting through extensive or dense green spaces is riskier since such spaces generate specific hazards. Green space-induced hazards include, but are not limited to, shaded road surfaces, surfaces made slippery by fallen, damp, or frost-covered leaves, fallen branches or trees, and sudden animal intrusions onto the road surface (Chen et al., 2020; Oddone Aquino & Nkomo, 2021). The risk of experiencing these events requires more commuter concentration and attention while commuting through green spaces, raising stress levels. Furthermore, the fear of missing out could serve as an explanation for the observed positive association describing anxiety and/or negative emotions people experience during undesirable activities and a possible lack of social interactions (Przybylski et al., 2013; Appel et al., 2019). Specifically, commuters may experience a sort of fear of missing out regarding their inability to engage with and enjoy the green spaces they encounter during their journeys to work as they are forced to leave for their jobs. This discrepancy between the reality of commuting and the desire to fully experience nature may contribute to increased stress levels.

We found that different operationalizations of the green space metric translated into varying green space-stress associations. By contrast, earlier work reported only minor differences in such possible translation (Helbich et al., 2021; Su et al., 2019). Regarding land use and cover-based measures, no widely accepted gold standard allows the aggregation of different cover classes into a single green space measure. Following previous practice (Bloemsma et al., 2022; Klompmaker et al., 2019), our metric included all forest and scrub vegetation. Denser green spaces, including such forest and scrub vegetation, may signify "enclosed" (i.e., low visibility) spaces, which are associated with increased perceived danger (Jorgensen et al., 2002; Maas et al., 2009; Sezavar et al., 2023). In turn, perceived danger may contribute to elevated stress. However, in our study, the average mean $NDVI_{LS}$ was below 0.45, and that of $NDVI_{SE}$ was approximately 0.50, both indicative of shrub vegetation (Aryal et al., 2022), typically perceived as open, with good visibility, and thus perceived as safer compared to enclosed green spaces (Jorgensen et al., 2002; Sezavar et al., 2023). Related to our results and partially aligned with previous findings (Reid et al., 2018), larger buffer sizes have tended to show stronger associations. Nonetheless, as in the case of the green space metric and echoing residence-based conclusions, there is also no universally agreed buffer size for route-based buffers, which may contribute to varying effect estimates. Scholarship continues to advance in determining the appropriate size for residential exposure buffers (Tian et al., 2024). How we can implement such advances in GPS- and commuting route-based research designs remains an open question.

4.3. Limitations and future research

Some limitations warrant acknowledgement. First, we could not consider whether participants commuted alone or with others, which could affect their travel experience, as suggested in transportation-related well-being studies (Liu et al., 2022; Staats & Hartig, 2004). Second, each participant was only measured once for stress with trip-specific environment exposure data aggregated to the personal level. As a result, there was a loss of potentially germane granularity in the data, potentially affecting the precision of the estimated effect size. Future studies could address this using ecological momentary assessment (Shiffman et al., 2008) involving real-time and near real-time sampling of participant behavior and experience and would permit accurate measurement of people's daily travel, well-being, and environmental experiences. Third, due to a lack of precise workplace addresses, we followed previous practices (Bohte & Maat, 2009; Chen et al., 2014; Wei et al., 2023b) and estimated both residential and work locations based on available GPS data, which may have introduced some classification errors. Likewise, the absence of semantic information regarding respondents' travel modes may have risked a classification bias in our rule-based approach. Fourth, travel mode choice varies by season (Ettema et al., 2017; Liu et al., 2015). We disregarded this aspect due to our limited sample size. We recommend that future studies explore possible seasonal variations in green space-mental health associations among commuters (Huang et al., 2024). Fifth, and the norm for GPS studies (Roberts & Helbich, 2021; Zhang et al., 2023), our GPS records may have limitations in accurately representing people's typical commuting behavior due to the signal reception (e.g., high buildings and tree canopy) and the relatively short tracking period. Future research designs may consider extending the tracking period (e.g., two weeks or one month) or applying potential future technologies to provide a more comprehensive understanding. Finally, causality inference could not be assigned as our data were observational.

5. Conclusions

Green space exposure along the commuting route was positively associated with commuters' stress. Operationalization of these exposure measurements and buffer sizes influenced exposure associations. We note that the employment of high-resolution data for green space assessment potentially allows a more accurate representation of commuters' experienced environments. Stratified analyses showed that the association between people's stress levels and green space exposure may also depend on the transport mode. Our findings suggest that uncovering the health implications of green space exposure should account for relevant behavioral contexts such as commuting.

CRediT authorship contribution statement

Jiakun Liu: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Lai Wei:** Writing – review & editing, Formal analysis. **Dick Ettema:** Writing – review & editing, Supervision, Conceptualization. **Marco Helbich:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data requests can be sent to the last author.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2024.105594.

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