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Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study

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ABSTRACT

Few studies go beyond the residential environment in assessments of the environment-mental health association, despite multiple environments being encountered in daily life. This study investigated 1) the associations between multiple environmental exposures and depressive symptoms, both in the residential environment and along the daily mobility path, 2) examined differences in the strength of associations between residential- and mobility-based models, and 3) explored sex as a moderator.

Depressive symptoms of 393 randomly sampled adults aged 18–65 were assessed using the Patient Health Questionnaire (PHQ-9). Respondents were tracked via global positioning systems- (GPS) enabled smartphones for up to 7 days.

Exposure to green space (normalized difference vegetation index (NDVI)), blue space, noise (Lden) and air pollution (particulate matter ($PM_{2.5}$)) within 50 m and 100 m of each residential address and GPS point was computed. Multiple linear regression analyses were conducted separately for the residential- and mobility-based exposures. Wald tests were used to assess if the coefficients differed across models. Interaction terms were entered in fully adjusted models to determine if associations varied by sex.

A significant negative relationship between green space and depressive symptoms was found in the fully adjusted residential- and mobility-based models using the 50 m buffer. No significant differences were observed in coefficients across models. None of the interaction terms were significant.

Our results suggest that exposure to green space in the immediate environment, both at home and along the daily mobility path, is associated with a reduction in depressive symptoms. Further research is required to establish the utility of dynamic approaches to exposure assessment in studies on the environment and mental health.

1. Introduction

Major depressive disorder is a leading contributor to disability worldwide (James et al., 2018). Global lifetime prevalence is 14.6%; in the Netherlands it is estimated to be slightly higher at 18.1% (Fedko et al., 2020). The disorder is characterised by sustained depressed mood, loss of interest or enjoyment and reduced energy (World Health Organization, 2017). Overall, this places a substantial burden on healthcare systems and results in high healthcare expenditure (König et al., 2020).

Recent studies have identified associations between green space, blue space, noise and air pollution and mental health (Klompmaker, Hoek, et al., 2019; Zhang et al., 2019). Greater surrounding green and blue space has been associated with lower incidence of depression (Groenewegen et al., 2018; McEachan et al., 2015; White et al., 2020). Moreover, research has shown that views of green and blue space from the home are also associated with improved mental health (Honold et al., 2016; White et al., 2020). Three pathways between green space, blue space, and health and well-being have been proposed: reducing harm (i.e. reducing exposure to environmental stressors), restoring capacities (e.g. attention restoration and stress reduction), and building capacities (e.g. facilitating physical activity or social cohesion) (Markevych et al., 2017; White et al., 2020).

In contrast, greater exposure to noise and air pollution has been associated with increased risk of depression (Braithwaite et al., 2019; Dzhambov & Lercher, 2019; Eze et al., 2020). The relationship between noise and poorer mental health may be mediated by noise annoyance,

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neighbourhood restorative quality, physical activity and sleep disturbance (Dzhambov et al., 2018; van den Bosch & Meyer-Lindenberg, 2019). Air pollution may influence neuroinflammation, neurotransmitter function, neural plasticity and oxidative stress, which in turn affects mental health (van den Bosch & Meyer-Lindenberg, 2019).

Previous research on the relationship between environmental exposures and health has traditionally taken a residential-based approach to exposure assessment. That is, exposure extent has been defined on the basis of administrative boundaries containing, or circular or network buffers around, the residential address (Klompmaker, Hoek, et al., 2019; Seidler et al., 2017; Triguero-Mas et al., 2015; Zijlema et al., 2016). A boundary centred on the residential address represents an overly simplistic context that may not be in line with the true spatial behaviour of a person. In reality, people typically encounter multiple environments outside of the home in the course of their daily routine, for example for work, education or leisure activities (Chaix, 2018). Discrepancies between the measured and true context can result in exposure misclassification and in turn, biased estimates (Culyba et al., 2018; Kwan, 2018).

Recent research has urged the need to address these limitations by advocating for mobility-based exposure assessments (Chaix, 2018; Helbich, 2018; Kestens et al., 2017). Approaches to this vary: options include activity surveys or travel diaries that include details on time spent in other locations (Cole-Hunter et al., 2018; Tang et al., 2018); however, this can be burdensome for a participant and affected by issues of memory recall. The development of global positioning systems (GPS) offers the possibility to collect high resolution spatiotemporal data (Birenboim & Shoval, 2016). Due to their growing ubiquity worldwide, it is increasingly possible to utilise smartphones with GPS capabilities. This reduces participant burden and allows for rich data collection while remaining unobtrusive (Boonstra et al., 2018; Tonne et al., 2017).

Emerging research has used GPS-enabled smartphones to examine the relationship between the natural environment and mood state (Beute & de Kort, 2018; Kondo et al., 2020; Li et al., 2018; Tost et al., 2019). However, these studies do not account for other environmental exposures, such as air pollution, with which the natural environment may be spatially correlated. The potential for confounding is therefore ignored. This has been addressed in limited research that uses residential-based environmental exposures (Klompmaker, Hoek, et al., 2019; Zhang et al., 2019), but to the best of our knowledge, this is the first study to consider the combined effects of multiple environmental exposures (namely, green space, blue space, noise and air pollution) along the daily mobility path on depressive symptoms.

There is some evidence that associations between green space, blue space and mental health may vary by sex (Gascon et al., 2015), but the differences are not well understood. Moreover, there is scarce research on the moderating role of sex in the relationships between noise, air pollution and mental health (Clark & Paunovic, 2018; Fan et al., 2020). Given the differences in the prevalence and symptomology of mental disorders between sexes (Riecher-Rössler, 2017), an investigation into associations between environmental exposures and depressive symptoms by sex was warranted.

The aim of this study was to investigate the combined associations of green space, blue space, noise and air pollution around the home and along the daily mobility path and depressive symptoms. Our second aim was to explore differences in the strength of associations between residential-based and mobility-based environmental exposures and depressive symptoms. Lastly, we investigated whether these associations varied by sex.

2. Materials and method

2.1. Study design and sample

We conducted an observational cross-sectional tracking study (Helbich, 2019). Data collection was a two-stage process, involving a survey and a GPS-tracking smartphone app. In September-November 2018, 45,000 people were invited via a letter from Statistics Netherlands to complete an online survey, “Mood and Living Environment”. Eligibility criteria for participation were: registered in the Dutch National Personal Records Database; aged 18–65; living in a private household; not sampled by Statistics Netherlands in the past 12 months. The sample was determined using stratified random sampling. The number of individuals to be selected from each municipality was guided by its population size; individuals were then randomly sampled. The survey included questions on, among others, mental health, demographics and socioeconomic status. 11,505 respondents completed the survey, representing a response rate of 25.6%.

To capture mobility-based exposure, a GPS-tracking smartphone app was utilised. Survey respondents who agreed to be approached again were invited via email to download a bespoke smartphone app. Respondents received the invitation up to two days after survey completion. An information letter and an app log-in code that ensured data could be linked between the survey and smartphone app were included. The app was available for Android phones only (version 4.4+). An iOS app was developed; however, as the app was designed for a restricted user base, it was not approved for distribution on the App store. 8,869 invitation emails were sent, and the total number of app downloads was 820.

Once downloaded, in-app permissions must be granted for the app to collect sensor data. 753 participants agreed to in-app permissions for the app to monitor location, 629 of which recorded at least one GPS measurement. Summary characteristics of participants who downloaded the app but did not agree to permissions or provide data can be found in Table S1. The app then ran in the background with no user interaction for the duration of data collection. User interaction was minimised as much as possible to reduce any changes in behaviour as a result of the app running.

2.2. App settings

Adaptive sampling intervals were determined through pretesting by the research team and personal contacts using a variety of smartphone brands. Perceived battery life change was discussed, and changes made to balance this concern with the aims of the study. The location sampling interval was 20 s, with extended time intervals if no relevant movement had been made (minimum 20 m). If there was no relevant movement after 30 min, location was checked every minute. If no relevant movement was recorded after one hour, then location was checked every two minutes. The app stopped recording after a cumulative total time of 7 days of data had been collected. Data were initially stored locally and then uploaded daily and stored on a secure server at Utrecht University.

2.3. Ethics and data privacy

The study protocol (Helbich, 2019) was approved by the Ethics Review Board of Utrecht University (FETC17–060).

2.4. Measures

2.4.1. Outcome

Depressive symptoms were measured using the Patient Health Questionnaire (PHQ-9) (Kroenke et al., 2001). Respondents were asked how often they have been bothered by problems such as, for example, “Little interest or pleasure in doing things”, and “Feeling down, depressed, or hopeless”, over the past two weeks. Response options range from 0 “Not at all” to 3 “Nearly every day”. Items were summed to produce a total score; a higher score indicates more depressive symptoms. The summed-item score has been shown to have good diagnostic performance for screening for depression (Manea & Gilbody, 2015). The internal consistency of the items was high (Cronbach’s alpha = 0.89).

2.4.2. GPS data

The GPS data was cleaned according to criteria that indicated it was not representative of participant mobility. First, we removed participants whose data indicated poor compliance to the study. We defined this as a participant having $<$2.5 times the median absolute deviation in terms of the number of observations (Leys et al., 2013). Participants were also removed if they had any GPS points outside of the Netherlands as we assumed this was not representative of a typical week.

Next, points with a speed of $>$ 200 km/hr were removed. We selected 200 km/hr as the maximum possible speed between points as it was deemed implausible that speeds above the stated threshold could be achieved. This is in line with previous Dutch studies on travel speed (Bohte & Maat, 2009). Further, GPS points located $>$50 m from the travel network were removed. While GPS accuracy ideally is between 5 m and 10 m, this can extend to over 50 m dependent on travel mode and in urban areas with high-rise buildings (Beekhuizen et al., 2013). The travel network (namely, roads, railways, pedestrian and bike paths) was obtained from a topographic map of the Netherlands (Kadaster TOP10NL, 2020). The distance between each GPS point and the nearest point on the network was calculated, and those with a value $>$50 m were removed. Following the GPS cleaning, the sample comprised 419 participants. For a full flow chart of participant selection and the GPS cleaning process, see Fig. S1 in the Supplementary Materials.

2.4.3. Environmental exposures

Environmental exposures were calculated according to concentric buffers of 50 m and 100 m around each GPS point and for each participants' home address. The home address of each respondent was obtained via register linkage in order to calculate residential-based exposure. Buffer sizes were selected on the basis of previous research (Mueller et al., 2020; Su et al., 2019), and are thought to represent an area that is immediately visible, or with which the participant has direct contact. GPS points that lay within 100 m of the German or Belgian border (size of the largest buffer) were excluded from analysis to avoid edge effects due to data being unavailable for these countries. 878 GPS points were removed (representing 0.08% of the points that were kept after cleaning).

2.4.4. Green space

Green space was operationalised using the Normalised Difference Vegetation Indices (NDVI) (Tucker, 1979), derived from Landsat 8 Operational Land Imager via the Google Earth Engine (GEE) cloud computing platform (Gorelick et al., 2017). NDVI describes the level of green biomass based on land surface reflectance of visible and near-infrared radiation using satellite imagery at a spatial resolution of 30 m $\times$ 30 m. Images were selected for the year 2018. Due to seasonal vegetation cycles, we only considered atmospherically corrected scenes collected during the growing season, namely May to September. To minimise the effects of clouds, we applied the GEE cloud score algorithm (Google Earth Engine, 2020). Scenes with $>$ 40% cloud cover and pixels with a cloud score of $>$ 25 were removed. Values range from -1 to 1 with higher values indicating greater density of vegetation, and negative values referring to non-biomass e.g., water bodies. Values $<$0 were excluded to avoid distortions when calculating the mean NDVI value per circular buffer.

2.4.5. Blue space

Blue space data was extracted from the Dutch land use database (Landelijk Grondgebruiksbestand Nederland; LGN) for 2018 (Hazeu et al., 2020). The database distinguishes 48 different land use types with a spatial resolution of 5 m $\times$ 5 m per raster cell. Proportion of blue space was calculated as the proportion of cells classified as fresh water or saltwater within the total number of cells in the circular buffer.

2.4.6. Air pollution

Annual average $PM_{2.5}$ concentrations (μg/m^3) were estimated for each buffer using maps derived from land use regression models (Eeftens et al., 2012; Schmitz et al., 2019). Annual average $PM_{2.5}$ concentrations were predicted by traffic intensity, traffic infrastructure, land use, and population density. $PM_{2.5}$ concentrations were resampled from a 5 m $\times$ 5 m to a 25 m $\times$ 25 m grid employing bilinear interpolation in order to reduce computational demand. The data refers to 2009, however, can be applicable to +/− 10 years as annual mean values are stable for multiple years (de Hoogh et al., 2018).

2.4.7. Noise pollution

Estimated average noise exposure from road, rail, air traffic, industry and wind turbines over a 24-hour period was obtained for 2016 from the Dutch National Institute for Public Health and Environment (RIVM) (Rijksinstituut voor Volksgezondheid en Milieu, 2019). Estimates were determined by the Standard Model Instrumentation for Noise Assessments (STAMINA), which was developed by the RIVM to map environmental noise in the Netherlands (Schreurs et al., 2010). The level of detail of the maps depend on the distance between the source and the observation point; the lowest resolution is 80 m $\times$ 80 m, and close to the source the resolution is 10 m $\times$ 10 m (Schreurs et al., 2010). The model has been applied in previous Dutch studies examining, among other exposures, the association between noise and health (Klompmaker, Janssen, et al., 2019). Estimates (in Lden (dB)) were grouped into nine day-evening-night noise classes, ranging from $<$ 45 dB to $>$ 80 dB. Estimates for each buffer were calculated by assigning a value of 1–9 to each class, weighting each value according to the proportion of the class found in the buffer, and summing.

2.4.8. Covariates

Control variables were available from the survey. We included age, sex, origin (Dutch, Western migration background, non-Western migration background), education (low, medium, high), employment status (employed, unemployed, non-working (i.e., incapacitated, student, homemaker, retired), other), marital status (married, separated/divorced, widow, never married), household type (couple with child, couple without child, single parent, other household type) and income quintile (1 = lowest, 5 = highest).

Population density, deprivation and social fragmentation were derived from Dutch population register data (Bakker et al., 2014), centred on the participants' home address at buffer sizes of 50 m and 100 m. Population density was operationalised by the number of inhabitants within the buffer on 1st January 2016. Deprivation was based on the unemployment rate, the standardised median household income (reverse coded), and the share of households with a standardised income below the poverty line. Social fragmentation was based on the percentage of adult residents ($>$18 years) who are unmarried, live in a single-person household, and who moved to their residential address in the last year. Input variables were z-scored and summed, with higher scores indicating greater social fragmentation or deprivation. Input data for the indices were from 1st January 2016. More recent years were unavailable.

2.5. Statistical analysis

Descriptive statistics were examined to explore the range and distribution of depressive symptoms and the environmental exposures. Wilcoxon tests were used to test for a statistical difference in PHQ-9 scores between the survey respondents and the final sample, and to assess the statistical significance of differences between the residential- and mobility-based exposures. Spearman correlations were produced to examine bivariate associations between the main variables. Generalized variance inflation factors (GVIF) were used to identify multicollinearity between exposures (Fox & Monette, 1992).

The structure of the data is such that the GPS points are nested within individuals, who each have a single outcome score. The environmental exposure data therefore must be aggregated to align the data to the same level. It has been suggested that the reduction in variability in the data when calculating the group mean can lead to biased parameter estimates and inaccurate estimates of standard errors (Croon & van Veldhoven, 2007). An alternative method has been proposed whereby a latent variable is produced from the explanatory variables at the lower level; in other words, the exposures associated with each GPS point are treated as indicators of the overall exposure variable for each individual (Croon & van Veldhoven, 2007). The unbiased group mean can then be used in an ordinary least squares regression with all variables aligned at the same level. Because the group sizes are different (i.e., varying number of GPS points per individual), this is implemented in conjunction with White's correction for heteroscedasticity.

We conducted separate multiple regression analyses using (1) the residential-based environmental exposures and (2) the mobility-based environmental exposures, at the 50 m and 100 m buffer level. Models were run with increasing levels of adjustment. In Model 1 a multi-exposure model was specified; green space, blue space, noise, and air pollution were entered only. In Model 2, we adjusted for the individual-based variables, namely: age, sex, education, employment, marital status, household type, origin, and income quintile. Finally, we added the social environment variables: population density, deprivation and social fragmentation. We considered these variables at two buffer sizes around the residential address: 50 m (Model 3a) and 100 m (Model 3b).

To explore the moderating role of sex, we compared fully adjusted models (using residential- and mobility-based exposures, at both buffer sizes) with and without an interaction term between PHQ-9 and sex, and statistically tested this using likelihood ratio tests. Where the likelihood ratio test was significant, results were stratified to examine differences between sex.

Unstandardised (*B*) and standardised (β) beta coefficients with (corrected) standard errors are reported. Following the recommendations of Gelman (2008), the regression coefficients were standardised by subtracting the mean of each input variable and dividing by twice the variable's standard deviation. This allows for regression coefficients to be comparable where there are also binary inputs (Gelman, 2008). Wald tests were conducted to test whether comparable coefficients for the environmental exposures were significantly statistically different between the fully adjusted residential- and mobility-based models. Reduction in Akaike's information criterion (AIC) of > 2 indicated substantial model improvement (Burnham & Anderson, 2004). For comparison, and following the conclusions of Foster-Johnson & Kromrey (2018), analysis was repeated using the observed means of the mobility-based exposures for each individual with White's correction for heteroscedasticity. Results were similar and model fit was not meaningfully improved (Table S2; Table S3). All analysis was conducted in R version 3.6.2 (R Core Team, 2019).

3. Results

3.1. Descriptive statistics

Table 1 summarises the characteristics of the final sample. The sample comprised participants who provided both residential and mobility-based environmental exposure data, no missing survey or register data, and met the GPS cleaning criteria. This led to a sample of 393 persons (3.4% of survey respondents). On average, each participant contributed 6.79 days of GPS data. Full details of participant selection can be seen in Fig. S1 in Supplementary Materials.

Mean PHQ-9 score was 5.08 (*SD*: 5.17). Wilcoxon tests showed there were no significant differences ($p = 0.508$) in PHQ-9 scores between the survey respondents and the final sample. The mean age of the sample was 44.56 (*SD*: 14.22), and the split between men and women was roughly equal (53.7% male). The majority of participants were employed (71.0%), highly educated (48.6%), of Dutch origin (89.8%) and in the second-highest or highest income quintile (60.8%). Mean population density was high (69.17 persons living within a 50 m radius of participant addresses), however, a large standard deviation (*SD*: 49.34) indicates a large variation in this.

Table 1
Characteristics of study population (n = 393).

	Category	n (%)
PHQ9 score (*M* (*SD*))		5.081 (5.17)
Age (*M* (*SD*))		44.56 (14.22)
Sex	Male	211 (53.7%)
	Female	182 (46.3%)
Employment status	Employed	279 (71.0%)
	Non-working	83 (21.1%)
	Other	11 (2.8%)
	Unemployed	20 (5.1%)
Education	Low	52 (13.2%)
	Medium	150 (38.2%)
	High	191 (48.6%)
Marital Status	Married	208 (52.9%)
	Separated	40 (10.2%)
	Unmarried	141 (35.9%)
	Widowed	4 (1.0%)
Household type	Couple with child	181 (46.1%)
	Couple without child	128 (32.6%)
	Single parent	18 (4.6%)
	Other household type	66 (16.8%)
Origin	Dutch	353 (89.8%)
	Western	29 (7.4%)
	Non-Western	11 (2.8%)
Income quintile	Very low	36 (9.2%)
	Low	39 (9.9%)
	Middle	79 (20.1%)
	High	120 (30.5%)
	Very high	119 (30.3%)
Population density (*M* (*SD*)) (50 m)		69.17 (49.34)
Population density (*M* (*SD*)) (100 m)		234.71 (144.23)
Social fragmentation (*M* (*SD*)) (50 m)		−0.06 (2.53)
Social fragmentation (*M* (*SD*)) (100 m)		−0.06 (2.42)
Deprivation (*M* (*SD*)) (50 m)		−0.05 (1.79)
Deprivation (*M* (*SD*)) (100 m)		0.06 (1.91)

Table 2 summarises the distribution of the residential-based and mobility-based exposures at the 50 m and 100 m buffer sizes. Exposure to green space was not significantly different between measurement types. Mean blue space, noise and $PM_{2.5}$ was greater for mobility-based exposures than for residential-based exposures, and these were confirmed to be significantly different ($p < 0.001$).

3.2. Bivariate analysis

Fig. S2 shows Spearman correlations between PHQ-9 and the environmental exposures. PHQ-9 was negatively, but weakly, significantly correlated with green space (all $p < 0.01$); correlations with each of the blue space measurements were non-significant. PHQ-9 was also significantly, yet weakly, positively correlated with both noise and $PM_{2.5}$ using the residential-based measurements only ($p < 0.05$).

Green space was consistently significantly negatively correlated with noise and $PM_{2.5}$ ($p = 0.001$). Noise and $PM_{2.5}$ were weakly to moderately correlated; correlations between blue space and the other exposures were largely non-significant.

For each environmental exposure, residential and mobility-based measurements were significantly correlated. Green space, blue space and noise were all somewhat moderately correlated ($r_s = 0.39$ to 0.66), whereas air pollution measurements were highly correlated, ranging from 0.80 to 0.84.

3.3. Regression analysis

The largest GVIF across all models was 1.82, indicating that multicollinearity between exposures was not an issue in analysis. A comparison of AIC values showed Model 2 consistently performed best (Table S3); adjusted R^2 values for Model 2 were moderate, ranging from 0.186

Table 2
Environmental exposure among study population.

	Residential-based (50 m) *M (SD)*	Mobility-based (50 m) *M (SD)*	*p* value	Residential-based (100 m) *M (SD)*	Mobility-based (100 m) *M (SD)*	*p* value
NDVI	0.360 (0.092)	0.362 (0.131)	0.821	0.370 (0.089)	0.374 (0.124)	0.473
Blue space	1.696 (4.817)	2.655 (7.468)	<0.001	2.434 (5.282)	3.218 (6.830)	<0.001
Noise (Lden (dB))	55.878 (5.529)	61.009 (8.704)	<0.001	56.061 (5.225)	60.294 (7.777)	<0.001
$PM_{2.5}$ (μg/m^3)	16.564 (0.721)	17.038 (1.168)	<0.001	16.582 (0.703)	16.933 (0.966)	<0.001

to 0.189.

Table 3 reports the models of associations between the environmental exposures and depressive symptoms according to the residential- and mobility-based exposure measures across 50 m and 100 m buffers, with increasing levels of adjustment. In our minimally adjusted models (Model 1), green space was significant for both residential- and mobility-based exposures and at both buffer sizes. Following adjustment for individual characteristics, the effect of green space was rendered non-significant. In the fully adjusted model (Model 3b), green space was significant in the residential- and mobility-based exposure models for the 50 m buffer only. Blue space, noise and $PM_{2.5}$ were not significantly associated with depressive symptoms in any of the models. Wald tests did not indicate any significant differences between comparable coefficients of the residential- and mobility-based environmental exposures across the fully adjusted models (Table S4).

3.4. Moderation analysis

We added interaction terms between the environmental exposures and sex separately, one at a time to fully adjusted models. No statistically significant interactions were observed; therefore, the models were not stratified further.

4. Discussion

4.1. Main findings

The purpose of this study was to examine associations between multiple environmental exposures, specifically green space, blue space, noise and air pollution, both at home and along the daily mobility path, and depressive symptoms. We also aimed to explore differences between the residential-based and mobility-based environmental exposures, and to investigate whether these associations varied by sex.

In our regression analyses, we observed a statistically significant negative relationship between greater exposure to green space and depressive symptoms in the minimally adjusted residential-based and mobility-based models, using both 50 m and 100 m buffers. This association was rendered non-significant following adjustment for individual characteristics. In our final fully adjusted model, the significant association between green space and depressive symptoms returned in both models for the 50 m buffer size only. No significant associations were observed between blue space, noise, and air pollution and depressive symptoms across all models.

We found that, on average, exposure to blue space, noise and air pollution was higher when using the mobility-based measure than the residential based measure. However, Wald tests demonstrated that the coefficients observed in the fully adjusted models did not differ significantly between the measurement types. Finally, we did not observe any statistically significant interactions between the environmental exposures and sex.

4.2. Available evidence

Principally, our findings underscore prior research that has consistently demonstrated an association between exposure to green space in the residential environment and depression (Klompmaker, Hoek, et al.,

Table 3
Multiple regressions for environmental exposures on depressive symptoms (n = 393).

	Residential-based						**Mobility-based**[a]					
	50 m			100 m			50 m			100 m		
	B	SE	β	*B*	SE	β	*B*	SE	β	*B*	SE	β
NDVI												
Model 1	−7.666**	2.922	−1.409**	−7.516*	3.102	−1.342*	−14.623**	4.482	−1.870**	−12.801**	4.582	1.651**
Model 2	−4.160	2.763	−0.765	−3.524	2.936	−0.629	−7.119	4.385	−0.911	−5.176	4.294	−0.668
Model 3a	−5.287	3.193	−0.971	−4.270	3.296	−0.763	−8.252	4.844	−1.055	−5.774	4.658	−0.745
Model 3b	−6.620*	3.304	−1.217*	−6.190	3.559	−1.106	−10.050*	5.355	−1.285	−7.621	5.247	−0.983
Blue space												
Model 1	−0.066	0.054	−0.633	0.005	0.049	0.056	−0.023	0.110	−0.122	−0.010	0.097	−0.057
Model 2	−0.046	0.051	−0.439	0.025	0.046	0.271	−0.008	0.085	−0.043	0.026	0.076	0.155
Model 3a	−0.043	0.051	−0.412	0.029	0.046	0.314	−0.006	0.086	−0.030	0.029	0.077	0.170
Model 3b	−0.045	0.049	−0.431	0.021	0.047	0.219	0.006	0.087	0.033	0.034	0.076	0.200
Noise												
Model 1	0.033	0.051	0.365	0.035	0.056	0.370	−0.033	0.080	−0.274	−0.022	0.083	−0.174
Model 2	−0.0009	0.049	−0.010	0.008	0.053	0.081	−0.048	0.082	−0.406	−0.032	0.085	−0.253
Model 3a	0.005	0.049	0.057	0.023	0.384	0.161	−0.044	0.083	−0.366	−0.026	0.087	−0.210
Model 3b	−0.005	0.049	−0.062	0.008	0.054	0.091	−0.051	0.082	−0.426	−0.030	0.086	−0.237
$PM_{2.5}$												
Model 1	0.345	0.393	0.498	0.491	0.407	0.690	0.099	0.488	0.143	0.173	0.519	0.233
Model 2	0.050	0.369	0.072	0.211	0.381	0.297	0.116	0.454	0.167	0.164	0.481	0.221
Model 3a	0.053	0.372	0.076	0.225	0.384	0.317	0.128	0.447	0.185	0.183	0.472	0.246
Model 3b	0.036	0.371	0.053	0.195	0.382	0.275	0.132	0.448	0.190	0.170	0.476	0.229

Note. Model 1: environmental exposures only; Model 2: Model 1 + age, sex, employment, education, marital status, household type, origin, income quintile; Model 3a: Model 2 + population density, social fragmentation and deprivation using 50 m buffer; Model 3b: Model 2 + population density, social fragmentation and deprivation using 100 m buffer. * = $p < 0.05$; ** = $p < 0.01$.

[a] Using adjusted means with White's correction for standard errors.

2019; McEachan et al., 2015; Triguero-Mas et al., 2015). Moreover, we went beyond previous research that was typically centred on the home to also take a mobility-based approach to exposure assessment. In this way we were able to confirm the currently limited research that has found a relationship between exposure to green space along the daily mobility path and mental health (Kondo et al., 2020; Li et al., 2018).

In our fully adjusted residential- and mobility-based models, the association between green space and depressive symptoms only held when applying the 50 m buffer size. No association was seen when using the 100 m buffer. This may be because a smaller buffer size is more closely aligned with what is visible and how the participant directly experiences the environment. This is supported by studies of street greenery and mental health (de Vries et al., 2013; Helbich et al., 2019; Wang et al., 2019). On the other hand, this contrasts with previous research that found improvements in mental health outcomes in relation to exposure to green space in the residential environment when using larger buffer sizes (Bos et al., 2016; Su et al., 2019).

In addition to green space, we also examined associations with blue space, noise, and air pollution. Such environmental exposures (including green space) are usually spatially correlated and few studies have considered their combined effects, therefore ignoring the potential for confounding (Gascon et al., 2017; Tzivian et al., 2015). We did not observe any significant associations with regards the other exposures. Our results are comparable to a previous study that examined the effect of multiple environmental exposures on depression, albeit the exposures were based on residential location: Klompmaker et al. (2019) report that in a multi-exposure model of antidepressant prescriptions, only green space within 300 m of the home was significant, with $PM_{2.5}$ and road traffic noise not reaching significance. Our findings highlight the need for future studies to control for multiple exposures where possible to avoid incorrectly estimating the effect of a single exposure.

We found no evidence that the strength of associations between the environmental exposures and depressive symptoms differed between residential- and mobility-based exposures. Our inconclusive results may be attributed to the way in which exposure along the daily mobility path was measured. For example, the choices made in terms of GPS data cleaning or aggregation may have affected our findings. Nevertheless, we did observe significant differences in means for blue space, noise and $PM_{2.5}$ between measurement types. Our findings supplement previous research that has observed significant differences in exposure to air pollution between residential location and mobility-based exposure (Dewulf et al., 2016; Nyhan et al., 2016; Setton et al., 2011), and further underscore the issue of exposure misclassification when only taking into account the residential environment (Culyba et al., 2018; Kwan, 2018).

We did not find any evidence that the associations between the environmental exposures and depressive symptoms varied by sex. The evidence for sex differences in the relationship between green space and mental health is inconsistent (Bolte et al., 2019; Van Den Berg et al., 2015). For example, a previous study on depression and anxiety in the Netherlands reported that a higher proportion of green space within 3 km of the home was associated with improved outcomes for women in the lowest (18–24) and highest age groups (≥65) only (Bos et al., 2016). In contrast, a study of four European studies found no evidence of moderation by sex between neighbourhood green space and mental health (Ruijsbroek et al., 2017). Our findings are therefore in agreement with (Ruijsbroek et al., 2017). We make a novel contribution to this discussion as the first to consider exposure to green space along the daily mobility path.

4.3. Strengths and limitations

This study advances current research as one of the first to go beyond residential-based exposures in the context of mental health. The use of GPS allowed for objective location data to be collected that was not affected by recall bias, and further demonstrates the feasibility of using GPS-enabled smartphones to capture dynamic environmental exposures. In this way, we have answered calls to expand the focus on residential neighbourhoods to a more person-centred approach (Chaix, 2018; Helbich, 2018). We were able to consider multiple environmental exposures along the daily mobility path, and we adjusted for a large number of control variables. Future research would do well to continue to push the capabilities of understanding dynamic environmental exposures using mobile sensor data, particularly with regard to integration of indicators of the social environment (Alexandre et al., 2020).

The study also has a number of limitations. Due to the cross-sectional nature of the data, we cannot rule out a reverse relationship whereby people with better mental health visit green space more. Experimental manipulation would be required to establish causality. Our outcome was based on self-reported data rather than objective diagnosis or prescription data, and this may have introduced bias. The survey data may be subject to selection bias, and highly educated and high-income persons were over-represented in our final sample. Therefore, our findings may not be generalisable to the general Dutch population.

The GPS data may have reduced accuracy in places where there are many tall buildings or dense canopy. However, we believe that these effects are negligible due to the flat terrain of the Netherlands and an absence of 'urban canyons'. In addition, we did not distinguish the GPS data by travel mode or whether the participant was indoors or outdoors. The effects of the environmental exposures may differ according to these different contexts. Moreover, we did not weight the mobility-based exposures by time spent in each location during aggregation. Spending more time in a location may be related to a stronger association between the environmental exposure and depressive symptoms. We also did not collect data on the environment as perceived by the participant. Participants may engage with or relate to certain environments in different ways, and this may affect the influence of the environment on their mental health (Kestens et al., 2017). This may be collected using ecological momentary assessment, however, it is not clear if this would alter participant responses or mobility patterns (Birenboim & Shoval, 2016). We aimed to minimise this issue by having almost no user interaction, but we cannot exclude the possibility that mobility patterns were altered without having comparable data prior to study inclusion.

Finally, as we could not meet the requirements of the App Store, we were unable to collect exposure data on iOS devices. At the time of data collection, Android represented on average 76.3% of the market share across the five main European markets (Kantar Worldpanel Comtech, 2019); we assume this is reflected within the Netherlands.

5. Conclusion

Our study finds that exposure to green space in the immediate environment is associated with a reduction in depressive symptoms. No associations were seen for blue space, noise, and air pollution. Residential- and mobility-based exposures were evaluated to be significantly different, however, this did not translate to a significant difference in the strength of associations with depressive symptoms. There was no evidence for sex as a moderator. Further research is required to determine the differences between residential- and mobility-based approaches to environmental exposure assessment and the implications for mental health.

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.

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CRediT authorship contribution statement

Hannah Roberts: Data Curation, Conceptualization, Methodology, Formal analysis, Visualization, Writing - Original Draft. **Marco Helbich:** Conceptualization, Methodology, Writing - Review & Editing, Project administration, Funding acquisition

Data availability statement

The data used in this analysis cannot be shared with third parties as per the policies of Statistics Netherlands. The syntax for the main analysis is available on Open Science Framework (https://osf.io/ygs72/).

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