Environmental Research 179 (2019) 108751

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Residential surrounding green, air pollution, traffic noise and self-perceived general health

Jochem O. Klompmaker[a,b,*], Nicole A.H. Janssen[a], Lizan D. Bloemsma[a,b], Ulrike Gehring[b], Alet H. Wijga[a], Carolien van den Brink[a], Erik Lebret[a,b], Bert Brunekreef[b,c], Gerard Hoek[b]

[a] National Institute for Public Health and the Environment (RIVM), Bilthoven, the Netherlands
[b] Institute for Risk Assessment Sciences (IRAS), Utrecht University, Utrecht, the Netherlands
[c] Julius Center for Health Sciences and Primary Care, University Medical Center Utrecht, Utrecht, the Netherlands

ARTICLE INFO

Keywords:
NDVI
NO_2
$PM_{2.5}$
Traffic noise
General health
Joint odds ratio

ABSTRACT

Self-perceived general health (SGH) is one of the most inclusive and widely used measures of health status and a powerful predictor of mortality. However, only a limited number of studies evaluated associations of combined environmental exposures on SGH. Our aim was to evaluate associations of combined residential exposure to surrounding green, air pollution and traffic noise with poor SGH in the Netherlands. We linked data on long-term residential exposure to surrounding green based on the Normalized Difference Vegetation Index (NDVI) and a land-use database (TOP10NL), air pollutant concentrations (including particulate matter (PM_{10}, $PM_{2.5}$), and nitrogen dioxide (NO_2)) and road- and rail-traffic noise with a Dutch national health survey, resulting in a study population of 354,827 adults. We analyzed associations of single and combined exposures with poor SGH. In single-exposure models, NDVI within 300 m was inversely associated with poor SGH [odds ratio (OR) = 0.91, 95% CI: 0.89, 0.94 per IQR increase], while NO_2 was positively associated with poor SGH (OR = 1.07, 95% CI: 1.04, 1.11 per IQR increase). In multi-exposure models, associations with surrounding green and air pollution generally remained, but attenuated. Joint odds ratios (JOR) of combined exposure to air pollution, rail-traffic noise and decreased surrounding green were higher than the odds ratios of single-exposure models. Studies including only one of these correlated exposures may overestimate the risk of poor SGH attributed to the studied exposure, while underestimating the risk of combined exposures.

1. Introduction

Self-perceived general health (SGH) is one of the most inclusive and widely used measures of health status (Jylhä, 2009; Benyamini, 2011). SGH is based on a simple question such as: "In general, would you say that your health is …". It differs from most measures of health insofar as its origins lies in a process that is not guided by formal, agreed rules or definitions (Jylhä, 2009). SGH is related with historic, current and future hospitalization and reflects comorbidity better than any additive measure of diseases (Benyamini, 2011; Nielsen, 2016). Further, several studies showed that SGH is a powerful predictor of mortality (Jylhä, 2009; Benyamini, 2011; Nielsen, 2016; DeSalvo et al., 2006; Mavaddat et al., 2014; Idler and Benyamini, 1997). SGH can be understood as a concise summary of information about conditions of the body and mind that in one way or another are involved in biological causative chains that may lead to death (Jylhä, 2009).

Living in greener areas has been associated with a lower risk of a poor SGH (Dadvand et al., 2016; Triguero-Mas et al., 2015; De Vries et al., 2003; Maas et al., 2006; Orban et al., 2017; de Vries et al., 2013). Only few studies investigated the association of air pollution or traffic noise with poor SGH (Brink, 2011; Halonen et al., 2014; Sun and Gu, 2008). However, air pollution and traffic noise have been linked to several chronic physical diseases and mental disorders (Power et al., 2015; Seidler et al., 2017; Vert et al., 2017; Fuks et al., 2017; Eze et al., 2015; Balti et al., 2014; Dzhambov, 2015; Hoek et al., 2013). A recently published study suggest that air pollution substantially impacts human health (Burnett et al., 2018) and reduces the mean life expectancy in Europe by about 2.2 years with an annual excess mortality rate of 790,000 in Europe (Lelieveld et al., 2019). Traffic-related noise exposure leads to a loss of at least one million healthy years of life every year in Europe (World Health Organization, 2011). As the proportion of people who live in urban areas is expected to increase within the next years (Rydin et al., 2012), more and more people will be exposed to high concentrations of air pollution and traffic noise levels and low

* Corresponding author. National Institute for Public Health and the Environment (RIVM), Antonie van Leeuwenhoeklaan 9, 3721 MA, Bilthoven, the Netherlands.
E-mail address: jochem.klompmaker@rivm.nl (J.O. Klompmaker).

https://doi.org/10.1016/j.envres.2019.108751
Received 24 June 2019; Received in revised form 16 September 2019; Accepted 16 September 2019
Available online 17 September 2019

levels of green.

None of the previously mentioned studies evaluated associations of combined exposure to green, air pollution and traffic noise with poor SGH. Residential green, air pollution and traffic noise are generally spatially correlated due to common sources of air pollution and road-traffic noise and the absence of these sources in green areas (Hystad et al., 2014; Thiering et al., 2016; Klompmaker et al., 2019a). Evaluation of associations of only one of these correlated environmental exposures, ignoring potential confounding by or interaction with the other two exposures, could lead to an overestimation of the true effect of that exposure. Our aim was to evaluate associations of combined long-term residential exposure to green, air pollution and road- and rail-traffic noise with poor SGH in a large national health survey. We specifically analyzed potential confounding, interaction and mediation between the three environmental exposures.

2. Methods

2.1. Study design and study population

We used data from a national health survey (Public Health Monitor, PHM *(Gezondheidsmonitor Volwassenen GGD-en, CBS en RIVM 2012)*) that included personal characteristics, lifestyle, socio-economic status (SES) and physical, mental and general health. The PHM was conducted by the 28 regional Public Health Services, Statistics Netherlands (CBS) and the National Institute for Public Health and the Environment (RIVM) in 2012. The elderly (≥65 years) were oversampled by design in the PHM. The PHM includes information on 387,195 citizens aged ≥19 years, the response rate was 47%. The addresses of all participants have successfully been geocoded.

Statistics Netherlands have enriched the PHM with information on standardized household income and region of origin. Standardized household income is household income that is adjusted for differences in household size and composition. The PHM was also linked with information on degree of urbanization and socio-economic status (SES) at the neighborhood level. Neighborhood SES represents the educational, occupational and economic status of the neighborhood. We used neighborhood SES information of 2010. Degree of urbanization is based on the average address density within a radius of 1 km (Den Dulk et al., 1992).

2.2. Outcome definition

We used the following question to define SGH: "In general, would you say that your health is …" with possible responses being: very good/good/moderate/poor/very poor. We dichotomized the answers, considering poor and very poor as "poor SGH".

2.3. Exposure assessment

For each subject, we assessed residential surrounding green, air pollution and traffic noise. Surrounding green was assessed in buffers with radii of 100, 300, 500, 1000, 3000 m for each address. We used the Normalized Difference Vegetation Index (NDVI) and a highly detailed national land-use database of the Netherlands of 2010 (TOP10NL, CC-BY Kadaster, 2010; https://www.kadaster.com/automatic-generalisation) to assess surrounding green. Surrounding green in closely related buffer sizes was highly correlated (spearman rho were generally ≥0.75) and associations between closely related buffer sizes, such as 1000 and 3000 m, barely differed. Hence, we focused on the 300 m and 1000 m buffers to limit the number of reported analyses.

Long-term average concentrations of particulate matter [PM (PM_{10}, PM_{coarse}, $PM_{2.5}$, $PM_{2.5}$abs)], NO_2 and two Oxidative Potential (OP) metrics – electron spin resonance (OP^{ESR}) and dithiothreitol (OP^{DTT}) - were assessed by land-use regression (LUR) models developed within the framework of the ESCAPE project (Beelen et al., 2013; Eeftens et al., 2012; Yang et al., 2015). Daily average (24 h, Lden) and night-time average (23:00–07:00 h, Lnight) road- and rail-traffic noise maps were assessed by the Standard Model Instrumentation for Noise Assessments (STAMINA) (Schreurs et al., 2010). The spatial resolution of the noise maps depends on the distance between source and observation point. The lowest resolution is 80 × 80 m and close to the source the level of detail is the highest, with a resolution of 10 × 10 m (Schreurs et al., 2010). As correlations between Lden and Lnight were high (spearman rho = 0.99 for road-traffic and 0.95 for rail-traffic), we only used Lden in our analyses.

More information about the assessment of exposure to surrounding green, air pollution and traffic noise can be found in the Supplement Methods (S1. Exposure assessment).

2.4. Exclusion of subjects

Since we did not have land-use data across the border of the Netherlands, subjects with residential addresses within 3000 m (largest buffer) of the border of the Netherlands were excluded from our database (8.4%), resulting in 354,827 subjects (Klompmaker et al., 2017).

2.5. Statistical analyses

Relationships between surrounding green, air pollution and traffic noise are complex. Air pollution and traffic noise reduction could be on the potential causal pathway of surrounding green to health, as green barriers may limit dispersion of traffic noise and air pollution or by scavenging of air pollution. These mechanisms, however, explain only part of the empirical relations of surrounding green with air pollution and traffic noise. More important is the fact that in a greener area, there are fewer sources of air pollution and traffic noise and consequently lower air pollution and noise levels. This reflects a common source (or the lack thereof) and thus not a causal pathway from surrounding green to health. Further, air pollution exposure is not on the causal pathway of traffic noise exposure to health and vice-versa.

We specifically analyzed potential confounding and interaction of long-term exposure to surrounding green, air pollution and traffic noise. In addition, we analyzed mediation to evaluate whether decreased levels of air pollution and traffic noise are possible mechanisms underlying potential beneficial associations of surrounding green with poor SGH. For the mediation analyses, we thus assumed that air pollution and traffic noise would be on the causal pathway from surrounding green to health, while for the confounding analyses we assumed that air pollution and traffic noise were not on the causal pathway from surrounding green to health. We used logistic regression analyses to study whether the environmental exposures were associated with poor SGH. All analyses were performed with R 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria) (R Core team, 2015).

2.5.1. Single-exposure regression models

We used single-exposure regression models to analyze individual associations of exposures with poor SGH. We specified *a priori* models with increasing degrees of covariate adjustment. Model 1 included age and sex. Model 2 was additionally adjusted for marital status, region of origin, paid occupation, standardized household income and level of education. Model 3 was additionally adjusted for neighborhood SES. Model 4 was additionally adjusted for smoking status and alcohol use. Model 5 was additionally adjusted for degree of urbanization. Categories of covariates in the regression analyses were identical to the categories presented in Table 1, except for age (12 categories: 19–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–74, 75–84, ≥85 years)and SES neighborhood (5 categories: quintiles).

In a cross-sectional study like ours, lifestyle factors can be a cause or a result of a poor SGH (Benyamini, 2011). Adjustment for these lifestyle factors can introduce a "cause-and-effect" bias: adjustment for these consequences of disease could lead to an attenuation of real effects

Table 1
Characteristics of the study population (n = 354,827).

	Characteristic	Category	n (%)
Covariates	Sex	female	193,782 (54.6)
	Age	19–39 years	68,940 (19.4)
		40–64 years	134,161 (37.8)
		≥65 years	151,726 (42.8)
	Marital status	married, living together	246,775 (70.6)
		unmarried/never married	42,233 (12.1)
		divorced	22,509 (6.4)
		widowed	38,089 (10.9)
	Region of origin	Dutch	308,167 (86.9)
		other western [a]	29,215 (8.2)
		other non-western [b]	6543 (1.8)
		Netherlands Antilles	1500 (0.4)
		Suriname	3820 (1.1)
		Turkey	3284 (0.9)
		Morocco	2298 (0.6)
	Education	primary or less	33,679 (9.8)
		Lower-secondary	119,549 (34.9)
		Higher-secondary	97,005 (28.3)
		University	92,733 (27.0)
	Paid occupation	yes	158,704 (48.1)
	Standardized household income	< €15,200	35,539 (10.1)
		€15,200–19,399	67,391 (19.1)
		€19,400–24,199	74,677 (21.2)
		€24,200–30,999	83,916 (23.8)
		≥ €31,000	91,224 (25.9)
	Smoking status	current	65,702 (19.7)
		former	133,267 (39.9)
		never	134,794 (40.4)
	Number of cigarettes smoked (mean (SD))	Number of cigarettes smoked/day for current smokers	10.2 (8.3)
	Alcohol use	current	280,311 (82.2)
		former	20,564 (6.0)
		never	40,007 (11.7)
	Alcohol consumption (mean (SD))	Number of alcohol glasses/week for current consumers	8.5 (9.6)
	BMI	< 18.5 kg/m^2	4628 (1.3)
		18.5–24.9 kg/m^2	154,595 (44.3)
		25.0–30.0 kg/m^2	130,058 (37.2)
		> 30.0 kg/m^2	59,987 (17.2)
	Physical activity	≤340 min/wk	83,340 (25.1)
		340–720 min/wk	86,401 (26.0)
		720–1380 min/wk	80,470 (24.2)
		> 1380 min/wk	81,634 (24.6)
	SES neighborhood (mean (SD))	Range: -6.9 – 3.0	0.06 (1.10)
	Degree of urbanization	Urban (≥1500 addresses/km2)	140,260 (39.5)
		Non-urban (< 1500 addresses/km2)	214,550 (60.5)
Outcome			
	Self-perceived general health	Poor + very poor	14,407 (4.1)

[a] Other western: Europe (excluding Turkey), North America, Oceania, Indonesia, Japan.
[b] Other non-western: Africa, Latin America, Asia (excluding Indonesia and Japan, including Turkey).Table.

(Seidler et al., 2017). Therefore, we evaluated the impact of adjustment for lifestyle separate from adjustment for generic individual and area-level SES variables (Model 4versus 3). Literature suggests potential bidirectional relations of poor health with lifestyle factors, such as cigarettes smoked and BMI (Johnson et al., 2000; Wu and Anthony, 1999; Chang et al., 2016; Boden and Fergusson, 2011; Luppino et al., 2010; Harvey et al., 2010; Keenan, 2009; Van Gool et al., 2007). We assumed that a change in smoking status (never, current, former) or alcohol use (never, current, former) due to poor health is less likely than a change in number of cigarettes smoked, alcohol consumption (glasses per week), physical activity and BMI. So, we decided to adjust for smoking status and alcohol use status in Model 4 and Model 5. As sensitivity analyses, we additionally added the number of cigarettes smoked, alcohol consumption (glasses per week), physical activity and BMI to Model 4 (Model 4b).

For each exposure, we specified a regression model with the exposure variable as linear term (1 degree of freedom). Additionally, we used natural splines (3 degrees of freedom) to determine the linearity of exposure-response curves. Exposure-response curves showed a non-significant or small to moderate deviation from linearity for most associations (Fig. S1). Deviations from linearity primarily occurred at (low or high) exposures where we had little data as evidenced by the wide confidence intervals of the non-linear part of most curves. We considered the deviations from linearity to be sufficiently large to present both linear and quintile analyses in the paper, but not large enough to make the linear analysis uninformative. We presented the linear association of exposure to surrounding green, air pollution and traffic noise per interquartile range (IQR) increase in exposure.

As the elderly were oversampled in the PHM, we performed stratified analyses to evaluate whether associations differ between the elderly (≥65 years) and the non-elderly (< 65 years).

2.5.2. Multi-exposure regression models

To evaluate potential mutual confounding of exposures, we specified multi-exposure regression models with combinations of surrounding green, air pollution and traffic noise exposure. We used generalized variance inflation factors (GVIFs) to quantify multicollinearity between the exposures (Fox and Monette, 1992).

As correlated exposure estimates share overlapping information, it can be difficult to disentangle individual effects of correlated exposures

in epidemiological studies. Hence, in exposure-health regression models, the estimated coefficient for one exposure based on a single-exposure model could be partly or fully explained (confounded) by the overlapping information with another exposure, depending on the extent of overlap (correlation) and the associations with the outcome. Therefore, the estimated coefficient for an exposure from a single-exposure model could be an overestimation of the "true" coefficient of that exposure. However, since no adjustment for the overlapping information with the other correlated exposure is made in a single-exposure model, the coefficient of the single-exposure model could be a good indication for the joint coefficient of both correlated exposures.

Using the Cumulative Risk Index (CRI) method (Crouse et al., 2015; Jerrett et al., 2013; Lippmann et al., 2013), we assessed joint coefficients (joint odds ratios, JORs) of surrounding green, air pollution and traffic noise exposures. As decreasing surrounding green is a risk factor, we evaluated the association of *decreased* surrounding green and *increased* concentrations of air pollution and levels of traffic noise. The JOR represents the odds for an IQR *increase* in air pollution and traffic noise and an IQR *decrease* for surrounding green exposure relative to the odds for no increase (decrease for surrounding green) in any of the exposures. The JORs are based on the estimates from a multi-exposure model. More information about the CRI can be found in the Supplement Methods (S2. Cumulative Risk Index).

To evaluate potential interactions of combined exposures, we specified interaction terms in two-exposure models. To be able to observe patterns of interactions, we assessed interactions by combining a continuous exposure with quintiles of another exposure and vice versa. Interactions were assessed on the multiplicative scale. Green is hypothesized to modify adverse effects of noise and air pollution on health (Dimitrova and Dzhambov, 2017). Therefore, we expected that the effect of air pollution or traffic noise is strongest (increased odds) in the lowest surrounding green quintile and that the effect of surrounding green is strongest (decreased odds) in the lowest air pollution or road-traffic noise quintile. Further, we hypothesized that the effect of exposure to air pollution is strongest (increased odds) in the highest road-traffic noise quintile and vice versa.

2.5.3. Mediation analyses

We performed mediation analyses to evaluate whether decreased levels of air pollution or traffic noise are possible mechanisms underlying potential beneficial effects of surrounding green on poor SGH. Here, we specified air pollution and traffic noise as mediators of the surrounding green – poor SGH associations and thus assumed a causal relationship between surrounding green and air pollution. Of the potential 'mediator' variables (air pollutants and traffic noise), we only selected the exposures that were significantly associated (increased ORs) with poor SGH for the mediation analyses.

We used the 'Mediation' package to calculate proportions mediated (Tingley et al., 2014). Mediators were added one at a time in the mediation analyses. Briefly, we specified mediator models (mediator = surrounding green + covariates) and outcome models (outcome = surrounding green + mediator + covariates) for each environmental exposure that was significantly associated with poor SGH (single-exposure models). Next, we included the model objects (mediator model and outcome model) in the mediate function and specified the "treat" (independent variable = surrounding green) and "mediator" variable. Further, we also ran mediation analyses with adjustments for the other environmental exposures (multi-exposure models), in both mediator and outcome models. In the mediation analyses, we assessed confidence intervals by 300 non-parametric bootstrap simulations. Due to computational limitations we were not able to run the recommended 1000 bootstrap simulations (Tingley et al., 2014).

3. Results

3.1. Study population and exposure distribution

Our study population consisted of 354,827 persons aged 19 years or older (Table 1). Due to oversampling of the elderly, almost 43% of the subjects were 65 years or older. Further, people of Dutch origin were overrepresented in the PHM (86.9% compared with 78% in the general population). More information about the PHM can be found elsewhere (Statistics Netherlands, 2015).

Of our study population, 4.1% reported a poor SGH. The prevalence of poor SGH in the most urbanized areas was almost twice as high as the prevalence in the least urban areas: 5.9% in strongly urbanized areas ($\geq$2500 addresses/km^2) versus 3.1% in non-urbanized areas (< 500 addresses/km^2).

The variation (IQR/median) in TOP10NL surrounding green space was larger than the variation in NDVI surrounding greenness (Table S1). The variation in $PM_{2.5}$ and PM_{10} levels was substantially smaller than the variation in the levels of the other pollutants, particularly NO_2 and $PM_{2.5}$abs. Road-traffic noise varied less than NO_2, but more than $PM_{2.5}$ and PM_{10} (Table S1). Surrounding green, air pollution and traffic noise exposures at the study participants' home address were overall moderately correlated (Fig. S2). NDVI surrounding greenness in a 300 m buffer (NDVI 300 m) was negatively correlated with NO_2 (−0.49) and road-traffic noise (−0.22). $PM_{2.5}$ was very weakly correlated with NDVI 300 m (−0.05) and positively correlated with road-traffic noise (0.23).

3.2. Single-exposure models

Associations of surrounding green, air pollution and traffic noise with poor SGH were affected by adjustments for covariates (Fig. S3). In our minimally adjusted models (Model 1, adjusted for age and sex), we found strong inverse associations of surrounding green and strong positive associations of air pollution and traffic noise with poor SGH. When marital status, region of origin, paid occupation, standardized household income and level of education were added (Model 2), associations with all exposures strongly attenuated. When neighborhood SES (Model 3), smoking status and alcohol use (Model 4) were added, associations slightly further attenuated but remained significant. The sensitivity analyses with adjustments for physical activity, BMI, number of cigarettes and alcohol consumption (Model 4b) showed attenuated associations of surrounding green with poor SGH. After adjustment for SES and lifestyle factors, additional adjustments for degree of urbanization (Model 5) barely affected associations. Therefore, we decided to present results of Model 5 in the remainder of the paper.

In Model 5, surrounding green was inversely associated with the odds of poor SGH (Table 2 and S2). We found an OR of 0.91 (95% CI: 0.89, 0.94) per IQR increase for NDVI 300 m. The strongest association was found with TOP10NL 1000 m (OR = 0.88, 95% CI: 0.84, 0.92). All air pollutants, except PM_{coarse}, were positively associated with the odds of poor SGH (Table 2 and S2). We found an OR of 1.07 (95% CI: 1.04, 1.11) per IQR increase for NO_2 and an OR of 1.05 (95% CI: 1.02, 1.07) per IQR increase for $PM_{2.5}$. Rail-traffic noise was weakly positively associated with poor SGH, while road-traffic noise was not (Table 2 and S2). Associations with poor SGH were slightly stronger for the elderly than for the non-elderly (Table S3). For example, for NO_2 we found an OR of 1.05 (95% CI: 1.00, 1.10) for the non-elderly and an OR of 1.09 (95% CI: 1.05, 1.14) for the elderly.

3.3. Multi-exposure models

We decided to use NDVI 300 m, NO_2 and $PM_{2.5}$ exposure in our multi-exposure models, as these are the most commonly studied exposures for surrounding green and air pollution respectively. In addition, we used TOP10NL 1000 m and OP^{DTT} as we found the largest ORs

Table 2
Odds ratios for associations of surrounding green, air pollution and traffic noise with poor self-perceived general health in single-exposure models [a].

	Exposure (IQR)	OR (95% CI)
Surrounding green	- NDVI 300 m (0.13)	0.91 (0.89, 0.94)
	- NDVI 1000 m (0.14)	0.93 (0.90, 0.95)
	- TOP10NL 300 m (0.24)	0.91 (0.88, 0.93)
	- TOP10NL 1000 m (0.32)	0.88 (0.84, 0.92)
Air pollution	- PM_{10} (1.24 μg/m^3)	1.03 (1.01, 1.06)
	- PM_{coarse} (0.82 μg/m^3)	1.01 (0.98, 1.03)
	- $PM_{2.5}$ (0.83 μg/m^3)	1.05 (1.02, 1.07)
	- $PM_{2.5}$abs (0.25 10^{-5}/m)	1.05 (1.03, 1.08)
	- NO_2 (7.85 μg/m^3)	1.07 (1.04, 1.11)
	- OP^{DTT} (0.27 nmol DTT/min/m^3)	1.09 (1.06, 1.13)
	- OP^{ESR} (0.18 A.U./1000/m^3) [b]	1.03 (1.01, 1.06)
Traffic noise	- Road-traffic noise [Lden] (7.5 dB)	1.01 (0.98, 1.03)
	- Rail-traffic noise [Lden] (8.9 dB)	1.02 (1.00, 1.05)

[a] Results are presented as OR (95% CI)) per interquartile range increase. Models were adjusted for sex, age, marital status, region of origin, education, paid occupation, standardized household income, neighborhood SES, smoking status, alcohol use and degree of urbanization.
[b] A.U. = arbitrary unit.

for these exposures. Further, rail-traffic noise but not road-traffic noise, was taken into account in multi-exposure models. Both TOP10NL and NDVI metrics were used to represent surrounding green; therefore, only one surrounding green exposure was included in the multi-exposure models. Both traffic noise exposures were taken into account in our interaction models. Multicollinearity of exposures was not an issue in our regression analyses (GVIF values were below 2.2).

3.3.1. Associations in multi-exposure models

In multi-exposure models, associations of surrounding green with poor SGH slightly attenuated when air pollution was added to the model (Table 3). Associations of NO_2 or OP^{DTT} with poor SGH attenuated more when surrounding green was added to the model. For example, the OR of NO_2 attenuated from 1.07 (95% CI: 1.04, 1.11) to 1.04 (95% CI: 1.01, 1.08) when adjusted for NDVI 300 m. Associations of $PM_{2.5}$ with poor SGH barely attenuated when surrounding green was added to the model. In multi-exposure models with combinations of two air pollutants, all pollutants remained significantly associated with SGH (Table 3). Associations of rail-traffic noise attenuated when adjusted for TOP10NL 1000 m (OR = 1.01, 95% CI: 0.99, 1.04).

The JORs of a combination of exposure to air pollution, rail-traffic noise and *decreased* surrounding green were always larger than the ORs of single-exposure models (Fig. 1). We found the largest JOR for a combination of exposure to $PM_{2.5}$, rail-traffic noise and *decreased* TOP10NL 1000 m (JOR = 1.19, 95% CI: 1.12, 1.26). However, differences between JORs based on two or three exposures were small.

We found no indications for multiplicative interactions in the hypothesized directions between combinations of exposure variables and poor SGH. Some Interaction terms were significant, but there was no clear pattern of interaction effects (Table S4). For example, an IQR increase in NO_2 in the lowest road-traffic noise quintile was associated with higher odds of poor SGH (OR = 1.12, 95% CI: 1.03, 1.22). In the highest road-traffic noise quintile, an IQR increase in NO_2 was not significantly associated with the odds of poor SGH (OR = 0.95, 95% CI: 0.87, 1.05), opposite to the hypothesized direction of the interaction.

3.4. Mediation analyses

We decided to only use NDVI 300 m, NO_2 and $PM_{2.5}$ in our mediation analyses. Assuming underlying assumptions of the mediation analyses hold, the association of NDVI 300 m with poor SGH was partly mediated by NO_2 (13%, 95% CI: 4, 27). $PM_{2.5}$ barely mediated the association of NDVI 300 m with poor SGH (1%, 95% CI: 0, 2).

4. Discussion

Our results suggest that surrounding green was inversely associated with poor SGH, while air pollution was positively associated with poor SGH. Rail-traffic noise was weakly positively associated with poor SGH, while road-traffic was not associated with poor SGH. In multi-exposure models, associations of surrounding green and air pollution attenuated mildly but remained significantly associated. JORs of combinations of exposure to air pollution and decreased surrounding green levels were higher than the ORs of single-exposure models.

4.1. Environmental exposures and poor self-perceived general health

Our observed associations of surrounding green with poor SGH are in line with previous studies (Dadvand et al., 2016; Triguero-Mas et al., 2015; De Vries et al., 2003; Maas et al., 2006; Orban et al., 2017; de Vries et al., 2013). Only a few studies evaluated associations of air pollution or traffic noise with poor SGH. Sun & Gu found positive associations of air pollution with poor SGH (Sun and Gu, 2008), similar to our findings. Brink found that traffic noise was not or very weakly associated with poor SGH (Brink, 2011), while Halonen et al. only found associations of road-traffic noise with poor SGH among men, but not among women (Halonen et al., 2014). The difference in associations with road- and rail-traffic noise might be due their temporal structures. Road-traffic noise is a more regular, continuous sound, while rail-traffic noise is characterized by more irregular and disruptive single noise events (Seidler et al., 2017). We speculate that people might habituate easier to road-traffic noise and experience road-traffic noise as less disruptive. It is unlikely that model quality is better for rail-traffic noise than for road-traffic noise. The correlation of SES neighborhood with

Table 3
Associations of environmental exposures with poor self-perceived general health in single- and two-exposure regression models [a].

Exposure (IQR)	Single exposure	Two exposure (adj. for) [b]					
		NDVI 300 m	TOP10NL 1000 m	PM2.5	NO2	OPDTT	Rail-traffic noise
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
NDVI 300 m (0.13)	0.91 (0.89, 0.94)	.	[c]	0.91 (0.89, 0.94)	0.92 (0.90, 0.95)	0.93 (0.90, 0.96)	0.91 (0.89, 0.94)
TOP10NL 1000 m (0.32)	0.88 (0.84, 0.92)	[c]	.	0.88 (0.85, 0.92)	0.89 (0.86, 0.94)	0.90 (0.86, 0.95)	0.88 (0.85, 0.92)
PM2.5 (0.83 μg/m^3)	1.05 (1.02, 1.07)	1.05 (1.02, 1.07)	1.04 (1.02, 1.07)	.	1.03 (1.01, 1.06)	1.03 (1.00, 1.05)	1.05 (1.02, 1.07)
NO2 (7.85 μg/m^3)	1.07 (1.04, 1.11)	1.04 (1.01, 1.08)	1.04 (1.00, 1.07)	1.06 (1.02, 1.10)	.	1.04 (1.00, 1.08)	1.07 (1.04, 1.11)
OPDTT (0.27 nmol DTT/min/m3)	1.09 (1.06, 1.13)	1.06 (1.02, 1.09)	1.05 (1.02, 1.09)	1.08 (1.04, 1.11)	1.07 (1.03, 1.11)	.	1.09 (1.05, 1.12)
Rail-traffic noise (8.9 dB)	1.02 (1.00, 1.05)	1.02 (1.00, 1.05)	1.01 (0.99, 1.04)	1.02 (1.00, 1.05)	1.02 (0.99, 1.04)	1.02 (1.00, 1.05)	.

[a] Results are presented as OR (95% CI) per interquartile range increase. Models were adjusted for sex, age, marital status, region of origin, education, paid occupation, standardized household income, neighborhood SES, smoking status, alcohol use and degree of urbanization.
[b] In all two-exposure models GVIF values were below 2.2.
[c] As TOP10NL and NDVI measures were used to represent surrounding green, we did not include both measures in a two-exposure model.

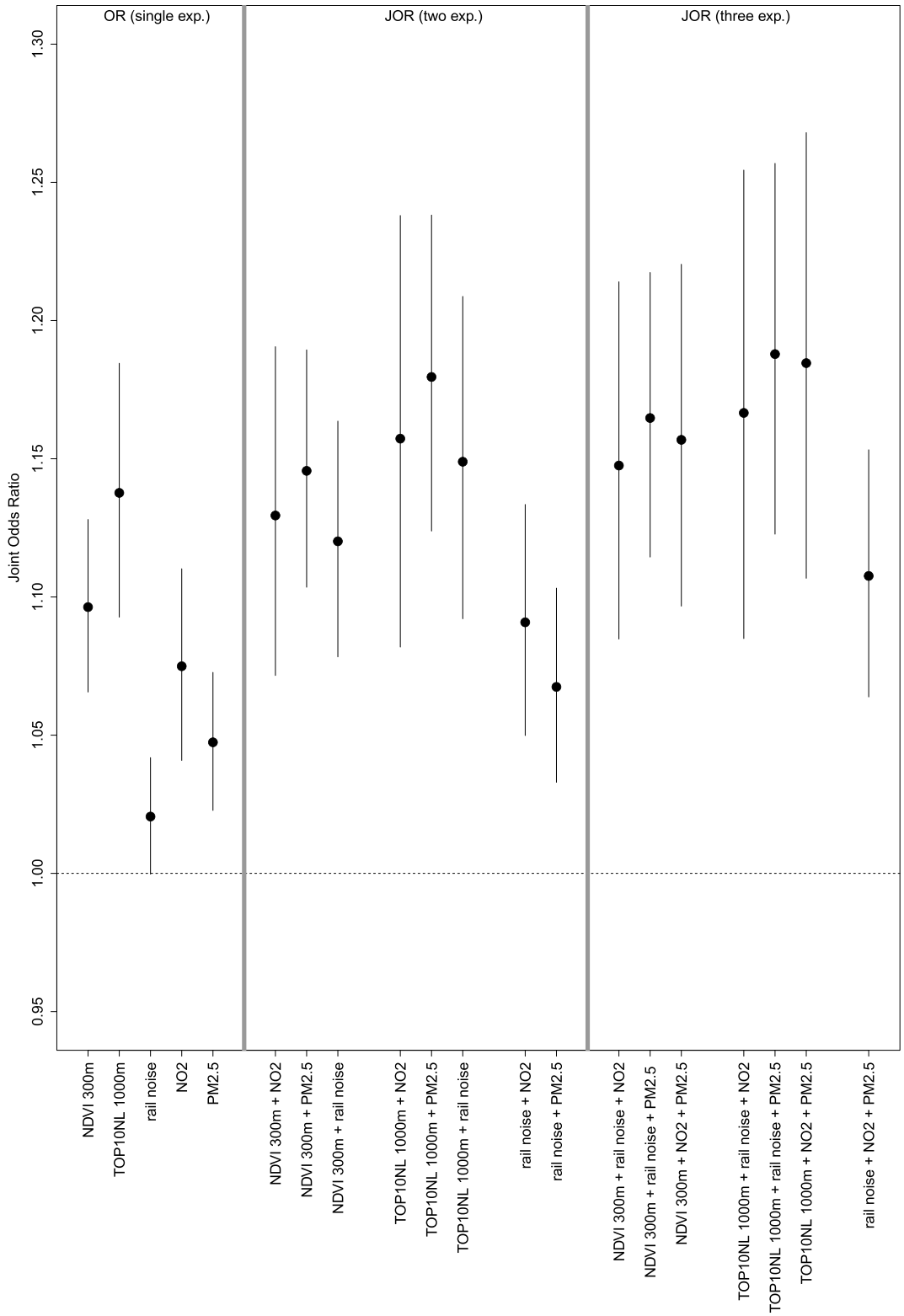

Fig. 1. JORs for associations of *decreased* surrounding green and *increased* air pollution and rail-traffic noise with poor self-perceived general health. Results are presented as OR (95% CI) per continuous increase/decrease (IQR for NDVI 300 m: 0.13, IQR for TOP10NL 300 m: 0.24, IQR for $PM_{2.5}$: 0.83 μg/m^3, IQR for NO_2: 7.85 μg/m^3, IQR for rail-traffic noise: 8.9 dB). Models were adjusted for sex, age, marital status, region of origin, education, paid occupation, standardized household income, neighborhood SES, smoking status, alcohol use and degree of urbanization. The ORs are based on estimates from single-exposure models; the JORs are based on estimates from multi-exposure models.

rail-traffic noise was similar compare to road-traffic noise, suggesting that potential residual confounding by SES is unlikely.

To our knowledge, no studies evaluated whether long-term exposure to a combination of surrounding green, air pollution and road- or rail-traffic noise was associated with poor SGH. We showed that associations of surrounding green were only slightly confounded by lower air pollution concentrations. This may be different in settings with a higher correlation between surrounding green and air pollution.

Further, we found associations of air pollution with poor SGH in single- and multi-exposure models. Adjustment for surrounding green did attenuate associations of NO_2 and OP^{DTT} but not of $PM_{2.5}$ with poor SGH. This is probably due to the fact that $PM_{2.5}$ was very weakly correlated with surrounding green, while NO_2 and OP^{DTT} were moderately correlated with surrounding green. Associations of NO_2 and OP^{DTT} adjusted for surrounding green became similar in magnitude to associations of $PM_{2.5}$ with poor SGH.

JORs of exposure to a combination of air pollution, rail-traffic noise and decreased surrounding green were always larger than the ORs of single-exposure models. This indicates that information about the risk of one exposure is only partly contained by the other correlated exposures and that the total effect of an intervention that affects air pollution, rail-traffic noise and surrounding green exposures is underestimated if only one of these exposures is taken into account to assess the effect. However, the individual effect of especially traffic-related air pollution (e.g. NO_2) on poor SGH is overestimated if one uses the OR of the single-exposure model.

For both elderly and non-elderly, surrounding green and air pollution were associated with poor SGH. However, associations were slightly stronger for the elderly than for the non-elderly. As elderly were oversampled in the PHM, associations reported for the full study population are probably an overestimation and therefore these associations may not be generalizable to the general Dutch population.

Adjustments for covariates attenuated associations between the environmental exposures and poor SGH. Associations strongly attenuated when individual SES variables, like standardized household income and education, were added to the model. This is plausible as SES is related to health in the Netherlands (Knoops and van den Brakel, 2010) and also to exposure levels. After adjustments for SES and lifestyle factors, adjustment for degree of urbanization barely affected ORs despite the clear relation between degree of urbanization and poor SGH. This suggests that the included individual and area-level SES variables were sufficient to adjust for the potential confounding by degree of urbanization. Adjustments for physical activity, BMI, number of cigarettes/day and alcohol consumption mainly affected associations of surrounding green. Due to the cross-sectional study design, we do not know whether these lifestyle factors are a cause or a result of poor SGH.

Assuming underlying assumptions of the mediation analyses hold, decreased NO_2 concentrations partly mediated the association of surrounding green on poor SGH, while $PM_{2.5}$ barely mediated the association. The choice to treat air pollution as confounder or mediator in the surrounding green – poor SGH association affects the effect size one should use to evaluate potential health impacts of surrounding green. If air pollution is assumed to be a confounder, the effect estimate (OR) of NDVI 300 m from a model with adjustment for NO_2 should be used. If air pollution is assumed to be a mediator, the effect estimate (OR) of the single-exposure model should be used and we expect that 13% of the association between NDVI 300 m and poor SGH may be related to reduced NO_2 concentrations.

SGH is based on the entire array of diseases and symptoms and may reflect on their objective characteristics as well as on subjective illness-wellness perceptions (Benyamini, 2011; Bishop and Yardley, 2010). Hence, associations of surrounding green and air pollution with poor SGH may be caused by the relation of these exposures with chronic physical diseases or poor mental health. Several longitudinal studies showed relations of surrounding green and air pollution with cardiometabolic health or poor mental health, such as diabetes, hypertension and depression (Fuks et al., 2017; Eze et al., 2017; Pun et al., 2018; Dalton et al., 2016; Miller et al., 2007; Cesaroni et al., 2014). We previously reported associations of surrounding green, air pollution and traffic noise with chronic physical diseases or poor mental health in this study population (Klompmaker et al., 2019a, 2019b). However, given the cross-sectional design of our study, we were not able to test whether these mechanisms underlie the associations of the exposures with poor SGH.

4.2. Strengths and limitations

We evaluated associations of multiple exposures (surrounding green, air pollution and traffic noise) on poor SGH in a large study population (> 350.000 subjects) with national coverage. Hence, we were able to study confounding and interaction effects of long-term residential exposure to surrounding green, air pollution and traffic noise. We used multiple indicators of surrounding green, air pollution and traffic noise exposure. All indicators were linked to the residential addresses of the subjects. All environmental exposures were assessed between 2009 and 2011, i.e. preceding and relatively close to the time the survey was administered (2012).

This study has a few limitations. Due to the cross-sectional study design, we do not know whether exposures preceded the outcome. Several studies have shown that the spatial variation of surrounding green, air pollution and traffic noise exposure levels remain stable over periods of about 10 years in highly developed western countries (Fecht et al., 2016; Eeftens et al., 2011; Cesaroni et al., 2012; Gulliver et al., 2011; Crouse et al., 2017; Vienneau et al., 2017). Hence, the current exposure estimates we used represent past exposure contrasts. Nevertheless, subjects may have moved. This residential mobility may lead to some exposure misclassification and subsequently biased associations with health outcomes. Further, we did not have time-activity data, which may also lead to exposure error and potentially an underestimation of the associations.

We performed a mediation analysis in a cross-sectional analysis. The general limitations of cross-sectional studies with regard to the temporality of exposure-response relationships do not apply to the mediation analysis, since we assessed mediation between environmental factors where the relationship is immediate. Further, we were not able to verify the underlying assumptions for the mediation analyses. We included a large number of potential confounders (individual SES, lifestyle factors and degree of urbanization) in our mediation analyses; hence we believe that the assumptions of no unmeasured confounding are reasonable.

We only had L_{den} and L_{night} values for road- and rail-traffic noise. Hence, we could not evaluate the impact of L_{day}, $L_{evening}$ and L_{night} separately. Further, the exposure models may differ in their accuracy to predict exposures. If LUR models predict air pollution exposure more precisely than the STAMINA model predicts traffic noise exposure, it could explain the more robust associations of air pollution exposures with poor SGH in this study. Performance of the LUR models differed between air pollutants and may have affected effect estimates. The weaker effect estimates for PM_{coarse} compared to other air pollutants could be due to a lower model performance. Further, NDVI and TOP10NL surrounding green measures do not incorporate the quality and type of green and may thus differ from perceived surrounding green exposure. For several proposed mechanisms of surrounding green, such as stress reduction, quality of green is likely important.

5. Conclusion

Our results suggest that surrounding green was inversely associated with poor SGH, while air pollution was positively associated with poor SGH. Rail-traffic noise was weakly positively associated with poor SGH, while road-traffic was not associated with poor SGH. The cumulative risk of exposure to a combination air pollution and decreased surrounding green may be underestimated by the risk of single-exposure models.

Competing financial interests

The authors declare that they have no actual or potential competing financial interests.

Acknowledgements

This research was carried out in the framework of , and funded by the RIVM Strategic Program (SPR; S/121004 HERACLES), in which expertise and innovative projects prepare RIVM to respond to future issues in health and sustainability. The Dutch Public Health Monitor 2012 (Gezondheidsmonitor Volwassenen GGD-en, CBS en RIVM) was conducted by 28 Public Health Services (GGD), Statistics Netherlands (CBS) and National Institute for Public Health and the Environment (RIVM). Statistical analyses were further facilitated by CBS.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2019.108751.

References

Balti, E.V., et al., 2014. Air pollution and risk of type 2 diabetes mellitus: a systematic review and meta-analysis. Diabetes Res. Clin. Pract. 106 (2), 161–172.
Beelen, R., et al., 2013. Development of NO 2 and NO x land use regression models for estimating air pollution exposure in 36 study areas in Europe–the ESCAPE project. Atmos. Environ. 72, 10–23.
Benyamini, Y., 2011. Why does self-rated health predict mortality? An update on current knowledge and a research agenda for psychologists. Psychol. Health 26 (11), 1407–1413.
Bishop, F., Yardley, L., 2010. The development and initial validation of a new measure of lay definitions of health: the wellness beliefs scale. Psychol. Health 25 (3), 271–287.
Boden, J.M., Fergusson, D.M., 2011. Alcohol and depression. Addiction 106 (5), 906–914.
Brink, M., 2011. Parameters of well-being and subjective health and their relationship with residential traffic noise exposure—a representative evaluation in Switzerland. Environ. Int. 37 (4), 723–733.
Burnett, R., et al., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. Proc. Natl. Acad. Sci. 115 (38), 9592–9597.
Cesaroni, G., et al., 2012. Nitrogen dioxide levels estimated from land use regression models several years apart and association with mortality in a large cohort study. Environ. Health 11 (1), 48.
Cesaroni, G., et al., 2014. Long term exposure to ambient air pollution and incidence of acute coronary events: prospective cohort study and meta-analysis in 11 European cohorts from the ESCAPE Project. BMJ 348, f7412.
Chang, S.-C., et al., 2016. Risk factors for late-life depression: a prospective cohort study among older women. Prev. Med. 91, 144–151.
Crouse, D.L., et al., 2015. Ambient PM2. 5, O3, and NO2 exposures and associations with mortality over 16 years of follow-up in the Canadian census health and environment cohort (CanCHEC). Environ. Health Perspect. 123 (11), 1180.
Crouse, D.L., et al., 2017. Urban greenness and mortality in Canada's largest cities: a national cohort study. Lancet Planet. Health 1 (7), e289–e297.
Dadvand, P., et al., 2016. Green spaces and general health: roles of mental health status, social support, and physical activity. Environ. Int. 91, 161–167.
Dalton, A.M., et al., 2016. Residential neighbourhood greenspace is associated with reduced risk of incident diabetes in older people: a prospective cohort study. BMC Public Health 16 (1), 1171.
De Vries, S., et al., 2003. Natural environments-healthy environments? An exploratory analysis of the relationship between greenspace and health. Environ. Plan. 35 (10), 1717–1732.
de Vries, S., et al., 2013. Streetscape greenery and health: stress, social cohesion and physical activity as mediators. Soc. Sci. Med. 94, 26–33.
Den Dulk, C., Van de Stadt, H., Vliegen, J., 1992. A new measure for degree of urbanization: the address density of the surrounding area. Maandstat. Bevolk. 40 (7), 14–27.
DeSalvo, K.B., et al., 2006. Mortality prediction with a single general self-rated health question. J. Gen. Intern. Med. 21 (3), 267.
Dimitrova, D.D., Dzhambov, A.M., 2017. Perceived access to recreational/green areas as an effect modifier of the relationship between health and neighbourhood noise/air quality: results from the 3rd European Quality of Life Survey (EQLS, 2011–2012). Urban For. Urban Green. 23, 54–60.
Dzhambov, A.M., 2015. Long-term noise exposure and the risk for type 2 diabetes: a meta-analysis. Noise Health 17 (74), 23.
Eeftens, M., et al., 2011. Stability of measured and modelled spatial contrasts in NO2 over time. Occup. Environ. Med. 2010, 061135.
Eeftens, M., et al., 2012. Development of land use regression models for PM2. 5, PM2. 5 absorbance, PM10 and PMcoarse in 20 European study areas; results of the ESCAPE project. Environ. Sci. Technol. 46 (20), 11195–11205.
Eze, I.C., et al., 2015. Association between ambient air pollution and diabetes mellitus in Europe and North America: systematic review and meta-analysis. Environ. Health Perspect. 123 (5), 381.
Eze, I.C., et al., 2017. Long-term exposure to transportation noise and air pollution in relation to incident diabetes in the SAPALDIA study. Int. J. Epidemiol. dyx020.
Fecht, D., et al., 2016. Spatial and temporal associations of road traffic noise and air pollution in London: implications for epidemiological studies. Environ. Int. 88, 235–242.
Fox, J., Monette, G., 1992. Generalized collinearity diagnostics. J. Am. Stat. Assoc. 87 (417), 178–183.
Fuks, K.B., et al., 2017. Long-term exposure to ambient air pollution and traffic noise and incident hypertension in seven cohorts of the European study of cohorts for air pollution effects (ESCAPE). Eur. Heart J. 38 (13), 983–990.
Gulliver, J., et al., 2011. Land use regression modeling to estimate historic (1962− 1991) concentrations of black smoke and sulfur dioxide for Great Britain. Environ. Sci. Technol. 45 (8), 3526–3532.
Halonen, J.I., et al., 2014. Associations of traffic noise with self-rated health and psychotropic medication use. Scand. J. Work Environ. Health 235–243.
Harvey, S.B., et al., 2010. Physical activity and common mental disorders. Br. J. Psychiatry 197 (5), 357–364.
Hoek, G., et al., 2013. Long-term air pollution exposure and cardio-respiratory mortality: a review. Environ. Health 12 (1), 43.
Hystad, P., et al., 2014. Residential greenness and birth outcomes: evaluating the influence of spatially correlated built-environment factors. Environ. Health Perspect. 122 (10), 1095–1102.
Idler, E.L., Benyamini, Y., 1997. Self-rated health and mortality: a review of twenty-seven community studies. J. Health Soc. Behav. 21–37.
Jerrett, M., et al., 2013. Spatial analysis of air pollution and mortality in California. Am. J. Respir. Crit. Care Med. 188 (5), 593–599.
Johnson, J.G., et al., 2000. Association between cigarette smoking and anxiety disorders during adolescence and early adulthood. Jama 284 (18), 2348–2351.
Jylhä, M., 2009. What is self-rated health and why does it predict mortality? Towards a unified conceptual model. Soc. Sci. Med. 69 (3), 307–316.
Keenan, P.S., 2009. Smoking and weight change after new health diagnoses in older adults. Archiv. Inter. Med. 169 (3), 237–242.
Klompmaker, J.O., et al., 2017. Green Space Definition Affects Associations of Green Space with Overweight and Physical Activity. Environmental Research.
Klompmaker, J.O., et al., 2019a. Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. Environ. Int. 129, 525–537.
Klompmaker, J.O., et al., 2019b. Associations of combined exposures to surrounding green, air pollution, and road traffic noise with cardiometabolic diseases. Environ. Health Perspect. 127 (8), 087003.
Knoops, K., van den Brakel, M.J.T., 2010. Rijke mensen leven lang en gezond, vol. 88. pp. 17–24 1.
Lelieveld, J., et al., 2019. Cardiovascular disease burden from ambient air pollution in Europe reassessed using novel hazard ratio functions. Eur. Heart J. 40 (20), 1590–1596.
Lippmann, M., et al., 2013. National Particle Component Toxicity (NPACT) Initiative: integrated epidemiologic and toxicologic studies of the health effects of particulate matter components. Res. Rep. (Health Effect. Inst.) (177), 5–13.
Luppino, F.S., et al., 2010. Overweight, obesity, and depression: a systematic review and meta-analysis of longitudinal studies. Arch. Gen. Psychiatr. 67 (3), 220–229.
Maas, J., et al., 2006. Green space, urbanity, and health: how strong is the relation? J. Epidemiol. Community Health 60 (7), 587–592.
Mavaddat, N., et al., 2014. Relationship of self-rated health with fatal and non-fatal outcomes in cardiovascular disease: a systematic review and meta-analysis. PLoS One 9 (7), e103509.
Miller, K.A., et al., 2007. Long-term exposure to air pollution and incidence of cardiovascular events in women. N. Engl. J. Med. 356 (5), 447–458.
Nielsen, T.H., 2016. The relationship between self-rated health and hospital records. Health Econ. 25 (4), 497–512.
Orban, E., et al., 2017. Residential surrounding greenness, self-rated health and interrelations with aspects of neighborhood environment and social relations. J. Urban Health 94 (2), 158–169.
Power, M.C., et al., 2015. The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. BMJ 350, h1111.
Pun, V.C., Manjourides, J., Suh, H.H., 2018. Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older US adults. Environ. Health 17 (1), 39.
Rydin, Y., et al., 2012. Shaping cities for health: complexity and the planning of urban environments in the 21st century. Lancet 379 (9831), 2079–2108.
Schreurs, E., Jabben, J., Verheijen, E., 2010. STAMINA-model Description. Standard Model Instrumentation for Noise Assessments.
Seidler, A., et al., 2017. Association between aircraft, road and railway traffic noise and depression in a large case-control study based on secondary data. Environ. Res. 152, 263–271.
Statistics Netherlands, 2015. Opbouw en instructie totaalbestand Gezondheidsmonitor Volwassenen 2012. Available from: https://www.cbs.nl/nl-nl/onze-diensten/methoden/onderzoeksomschrijvingen/korte-onderzoeksbeschrijvingen/gezondheidsmonitor.
Sun, R., Gu, D., 2008. Air pollution, economic development of communities, and health status among the elderly in urban China. Am. J. Epidemiol. 168 (11), 1311–1318.
R Core Team, 2015. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria 2016. http://www.R-project.org.
Thiering, E., et al., 2016. Associations of residential long-term air pollution exposures and satellite-derived greenness with insulin resistance in German adolescents. Environ. Health Perspect. 124 (8), 1291.
Tingley, D., et al., 2014. Mediation: R Package for Causal Mediation Analysis.
Triguero-Mas, M., et al., 2015. Natural outdoor environments and mental and physical health: relationships and mechanisms. Environ. Int. 77, 35–41.
Van Gool, C.H., et al., 2007. Chronic disease and lifestyle transitions: results from the longitudinal aging study amsterdam. J. Aging Health 19 (3), 416–438.
Vert, C., et al., 2017. Effect of long-term exposure to air pollution on anxiety and

depression in adults: a cross-sectional study. Int. J. Hyg Environ. Health 220 (6), 1074–1080.
Vienneau, D., et al., 2017. More than clean air and tranquillity: residential green is independently associated with decreasing mortality. Environ. Int. 108, 176–184.
World Health Organization, 2011. Burden of disease from environmental noise: quantification of healthy life years lost in Europe. In: Burden of Disease from Environmental Noise: Quantification of Healthy Life Years Lost in Europe, 126-126.
Wu, L.-T., Anthony, J.C., 1999. Tobacco smoking and depressed mood in late childhood and early adolescence. Am. J. Public Health 89 (12), 1837–1840.
Yang, A., et al., 2015. Spatial variation and land use regression modeling of the oxidative potential of fine particles. Environ. Health Perspect. 123 (11), 1187.