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Outdoor light at night, air pollution and depressive symptoms: A cross-sectional study in the Netherlands

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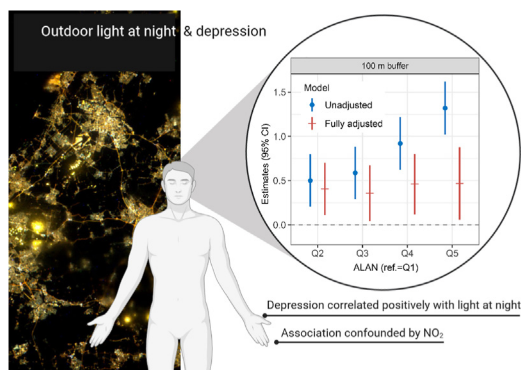
HIGHLIGHTS

- People's mental health may be susceptible to artificial light at night (ALAN).
- Satellite-measured outdoor ALAN was correlated with traffic-related exposures.
- Unadjusted models showed associations with ALAN but were strongly confounded.
- Depression severity correlated positively with NO_2 concentrations and neighborhood deprivation.
- Epidemiological assessments of outdoor ALAN should be adjusted accordingly.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Artificial light at night (ALAN) may be an anthropogenic stressor for mental health disturbing humans' natural day–night cycle. However, the few existing studies used satellite-based measures of radiances for outdoor ALAN exposure assessments, which were possibly confounded by traffic-related air pollutants.
Objectives: To assess 1) whether living in areas with increased exposure to outdoor ALAN is associated with depressive symptoms; and 2) to assess the potential confounding effects of air pollution.
Methods: We used cross-sectional data from people ($N = 10{,}482$) aged 18–65 years in the Netherlands. Depressive symptoms were assessed with the Patient Health Questionnaire (PHQ–9). Satellite-measured annual ALAN were taken from the Visible Infrared Imaging Radiometer Suite. ALAN exposures were assessed at people's home address within 100 and 600 m buffers. We used generalized (geo)additive models to quantify associations between PHQ–9 scores and quintiles of ALAN adjusting for several potential confounders including $PM_{2.5}$ and NO_2.
Results: Unadjusted estimates for the 100 m buffers showed that people in the 2nd to 5th ALAN quintile showed significantly higher PHQ–9 scores than those in the lowest ALAN quintile ($\beta_{Q2} = 0.503$ [95% confidence intervals (CI): 0.207–0.798], $\beta_{Q3} = 0.587$ [95% CI: 0.291–0.884], $\beta_{Q4} = 0.921$ [95% CI: 0.623–1.218], $\beta_{Q5} = 1.322$ [95% CI: 1.023–1.620]). ALAN risk estimates adjusted for individual and area-level confounders (i.e., $PM_{2.5}$, urbanicity, noise, land-use diversity, greenness, deprivation, and social fragmentation) were attenuated but remained significant for the 100 m buffer ($\beta_{Q2} = 0.420$ [95% CI: 0.125–0.715], $\beta_{Q3} = 0.383$ [95% CI: 0.071–0.696], $\beta_{Q4} = 0.513$ [95% CI: 0.177–0.850], $\beta_{Q5} = 0.541$ [95% CI: 0.141–0.941]). When adjusting for NO_2 per 100 m buffers, the air pollutant was associated with PHQ–9 scores, but ALAN did not display an exposure-response relationship. ALAN associations were insignificant for 600 m buffers.

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Conclusion: Accounting for NO_2 exposure suggested that air pollution rather than outdoor ALAN correlated with depressive symptoms. Future evaluations of health effects from ALAN should consider potential confounding by traffic-related exposures (i.e., NO_2).

1. Introduction

Light pollution emitted through anthropogenic sources including streetlights and billboards alters natural light levels (Levin et al., 2020). With about 88% of Europe affected by light-polluted nights (Falchi et al., 2016), outdoor artificial light at night (ALAN) is recognized as a pervasive environmental threat stressing ecosystems (Davies and Smyth, 2018) and human health alike (Haim and Zubidat, 2015; Cho et al., 2015; Fonken and Nelson, 2014).

Speculations arise that overexposure of ALAN is among those man-made disturbances contributing to multiple pathologies in humans (e.g., cancer [James et al., 2017]) by disrupting the circadian rhythm. Given that mental illness may reduce disability-adjusted life-years by as much as 13% (Vigo et al., 2016), a critical question is whether exposure to ALAN could also be involved in the development of mental illness. Laboratory animal studies suggest that aberrant exposure to ALAN provokes depressive-like responses and circadian rhythm perturbations (Bedrosian et al., 2013; LeGates et al., 2012; Fonken and Nelson, 2013). Its plausible that humans develop similar physiological and psychological responses to light polluted external environments (Lambert et al., 2015; Aries et al., 2015). For example, a study in Japanese elderly indicated associations between bedroom-measured light levels and depressive symptoms (Obayashi et al., 2013; Obayashi et al., 2018).

There have been few analyses of the association between outdoor ALAN and mental health. Findings from South Korea, for example, showed an association between depression symptoms and outdoor ALAN in adults (Min and Min, 2018). However, the analyses had been poorly adjusted for physical (Gong et al., 2016; Klompmaker et al., 2019) and social residential environmental correlates (Bagheri et al., 2020; Dowdall et al., 2017), had used first-generation ALAN data with technical restrictions (e.g., a lack of radiance calibration, a coarse resolution of 5 km) (Levin et al., 2020), and ALAN data were aggregated to a few administrative units, likely resulting in an exposure misclassification (Helbich, 2018). In addition, evaluations of satellite-assessed outdoor ALAN indicated that it may represent a poor proxy for indoor or personal ALAN exposure (Rea et al., 2011; Huss et al., 2019), and that high correlations with traffic-related air pollutants may exist in urban environments (Huss et al., 2019; Fecht et al., 2015). Air pollution has been previously associated with poor mental health (Braithwaite et al., 2019; Buoli et al., 2018) and should thus be accounted for when evaluating associations with satellite-measured ALAN to exclude that possibly other environmental exposures drive observed correlations.

To address these research gaps, we examined the associations between outdoor ALAN and depressive symptoms using nationally representative data from the Netherlands. We tested the hypotheses that 1) there is a positive association between exposure to ALAN and depression symptoms, and that 2) risk estimates are affected by adjusting for numerous potential confounders, in particular, air pollution (e.g., NO_2). It is important to disentangle how mental health correlates with ALAN because nighttime lighting is expected to further increase due to on-going urbanization; at the same time, air pollution is pervasive.

2. Methods

2.1. Study design and participants

We conducted an observational, cross-sectional study in the Netherlands. For two reasons the Dutch context provides an ideal setting: 1) it is among the highest ALAN polluted countries in Europe (Falchi et al., 2019), and 2) it displays the second greatest prevalence of mental illness in Europe. As many as 18% of residents in the Netherlands experience poor mental health (OECD, 2018).

This study was embedded in the NEEDS project, which is described elsewhere (Helbich, 2019). Briefly, a survey was conducted between September and December 2018 in conjunction with Statistics Netherlands. Participants completed an online survey on people's mental health (e.g., depression, anxiety), demographics, etc. Eligibility criteria for participant recruitment were: a) registered in the Dutch National Personal Records Database, b) aged between 18 and 65 years, c) not living in institutions and care homes, and d) not sampled by Statistics Netherlands in the past year. To receive representative data, a sample of 45,000 people were drawn from the population complying with the eligibility criteria using multi-stage sampling. We used incentives and three contacts (one invitation and two reminders) to increase survey participation. Of those invited, 11,505 completed the survey resulting in a response rate of 25.6% (Supplementary Fig. S1).

We obtained coordinates of resident's home addresses by matching survey data with registers from Statistics Netherlands and the land registry from 2018. All addresses were successfully geocoded. We excluded respondents not living on the mainland or living within 600 m of the German or Belgian border to avoid boundary effects ($N = 100$). Participants with incomplete data were also removed ($N = 923$), resulting in a final sample of 10,482.

The study design was approved by the Ethics Committee at Utrecht University (FETC17-060). Informed consent was implied when people completed the survey. Survey data were anonymized and enriched with registers. In line with Dutch privacy legislation, register data were non-publicly accessible for scientific research in the secure environment of Statistics Netherlands.

2.2. Depressive symptoms as outcome

Symptoms of depression were assessed through the self-administered Patient Health Questionnaire (PHQ–9) (Kroenke and Spitzer, 2002). Meta-analyses have ascribed the PHQ–9 good diagnostic performance to screen for depressive symptoms (Manea et al., 2015). Subjects responded to nine multiple-choice items that measured their mood levels over the prior two weeks. The response scale ranged from "not at all" (0) to "nearly every day" (3). The degree of depressive symptoms was calculated by summing individual item scores. This summative score can range between 0 and 27 with higher scores referring to more pronounced symptoms. A Cronbach's alpha of 0.887 indicated high internal consistency of the PHQ–9 in our sample.

2.3. Alan exposure assessment

ALAN exposure assessments were based on earth-observing satellites (Levin et al., 2020). We used globally calibrated remote sensing-based outdoor measurements from the Day/Night Band on the Visible Infrared Imaging Radiometer Suite (VIIRS) for 2016 (the most recent release) obtained from the National Oceanic and Atmospheric Administration (Elvidge et al., 2017). The sensor's radiometric sensitivity allows detecting even low levels of visible and near-infrared nightlight emitted from human settlements (e.g., street lights) (Miller et al., 2013). VIIRS data have a ground resolution of 750 m, which is higher than other remotely sensed ALAN products (Elvidge et al., 2017; Miller et al., 2013).

We used the annual composite to minimize the seasonal effects of emitted ALAN levels (Levin et al., 2020). Annual data ranging from 500 to 900 nm wavelength (with a radiance of nW/cm^2/sr) were preprocessed by filtering abnormal strong light sources (e.g., fires), removing outliers, and removing non-light background values (Elvidge et al., 2017). We used bilinear interpolation to down-sample ALAN data to 50 m to better align with other environmental data. Due to abnormally high values (e.g., through the presence of glasshouses), cells were restricted to values of >300 nW/cm^2/sr.

We applied concentric buffers of 100 and 600 m centered on respondents' home addresses to capture the immediate and extended surroundings at people's residential location. Average exposures to ALAN radiances per buffer were assigned to each respondent. To facilitate comparisons with previous studies (Min and Min, 2018), ALAN data were grouped into quintiles.

2.4. Covariates

Gender and ethnicity (Dutch, Western background, non-Western background) were included due to a varying prevalence in depression (Jorm, 2000; Stronks et al., 2009). Age in years was included because depression risk is life-time dependent (Malhi and Mann, 2018). Marital (married, separated/divorced, widowed, unmarried) and family status (single parent, couple without children, couple with children, other household types) status were coded as categorical variables. Marital disruption, for example, puts people at-risk (Kessler and Bromet, 2013). Because labor market absence impacts psychosocial well-being and life satisfaction (Paul and Moser, 2009), we distinguished between employed, unemployed, non-working, and other. To account for people with less education or lower socioeconomic status being at-risk of depression (Helbich et al., 2020), we included educational background coded into low (up to lower secondary education), medium (up to upper secondary education), and high (university education and further). Household income in quintiles (1 = lowest, 5 = highest) was obtained from registers; the most recent data were from 1st January 2016.

Area-level covariates were considered at both 100 and 600 m buffers. We aggregated individual register data for 2016 per buffer size to obtain urbanicity, deprivation, and social fragmentation. To adjust for urban-rural differences in psychiatric disorders (Peen et al., 2010), we included the number of inhabitants per buffer. Composite measures of deprivation (unemployment rate, reversely coded standardized median household income, the share of households with a standardized income below the poverty line) and social fragmentation (percentage of residents >18 years who were unmarried, lived in a single-person household, and had moved to the address in the previous 12 months) were developed by summing multiple *z*-scored variables (Hagedoorn et al., 2020). Pronounced social fragmentation reflects poor community integration putting people at-risk of poor mental health (Bagheri et al., 2020). The Shannon index, based on each buildings' use for 2018 from the land registry, was used as a land-use diversity score (Zock et al., 2018). Air pollution (Braithwaite et al., 2019) and noise (Dzhambov and Lercher, 2019) are depression risk factors. We incorporated annual average concentrations of particulate matter with an aerodynamic diameter of <2.5 μm ($PM_{2.5}$) and nitrogen dioxide (NO_2) (μm/m^{-3}) (Schmitz et al., 2019). The underlying land-use model was calibrated for 2009 but annual mean air pollution concentrations were stable over a decade (De Hoogh et al., 2018). Data on estimated average noise exposures emitted from roads, rail, aviation, industry, and wind turbines over a 24-h period were included (Rijksinstituut voor Volksgezondheid en Milieu, 2019). Noise estimates were grouped into six day–evening–night noise classes ranging from <45 dB to >65 dB. Data on greenness were obtained from the updated version of the Dutch land use model for 2015. We grouped the 39 land use types (e.g., forests, agricultural and natural areas) per 25 m grid cell to categorize the availability of greenness (%) (Zock et al., 2018).

2.5. Statistical analysis

We used descriptive statistics to summarize the data (i.e., mean [μ], standard deviation [SD]). Urban-rural differences were tested with Chi^2 tests for categorical variables and Kruskal-Wallis tests for continuous ones. We used a dummy for stratification into urban (at least moderately urbanized with ≥1000 addresses/km^2) and rural areas (hardly/not urbanized with <1000 addresses/km^2). Generalized variance inflation factors (GVIF) assessed multicollinearity. GVIFs >4 were deemed as problematic. Non-parametric Spearman correlation coefficients were used to assess bivariate associations.

We fitted generalized (geo)additive models (GAM) (Wood, 2017) with a Gaussian probability distribution to assess PHQ–9-ALAN associations, including a priori defined person- and area-level adjustments. To adjust for potentially unmeasured factors that are shared by respondents living close together, we considered the use of a bivariate soap film smoother on respondents' address coordinates. This approach accounts for the complex shape of our study area without smoothing beyond its boundary (Wood et al., 2008). We used a 5000 m grid of interior knots to set-up the soap film smoother (Supplementary Fig. S2).

Four models with different levels of adjustment were estimated with restricted maximum likelihood. Model 1 was unadjusted by only considering ALAN. Model 2 was additionally adjusted for person-level characteristics. Model 3 was additionally adjusted for area-level characteristics, and Models 4 additionally included a soap film smoother. Model 1–4 were then fitted with buffer sizes of 100 and 600 m. Goodness-of-fits were compared with the deviance explained and the Akaike information criterion (AIC). Higher deviance and lower AIC scores refer to a better fit with AIC reductions of >2 describing substantial model improvement (Burnham and Anderson, 2003). Residual spatial autocorrelation was tested with empirical semivariograms that were bootstrapped 999 times. The GAMs were fitted with the mgcv library (1.8–31) in R 3.6.2 (64 bit) (R Core Team, 2019).

2.6. Sensitivity analyses

GAMs were separately fitted for urban and rural areas using the urban-rural dummy variable (Model 5–6). Because ALAN correlated strongly with NO_2 (Huss et al., 2019), we repeated our analyses with an adjustment for NO_2 rather than $PM_{2.5}$ (Model 7). Finally, to test the influence of exposure misclassification due to residential mobility, we restricted the observations to those who had lived at least one year at their current place of residence (Model 8).

3. Results

3.1. Descriptive statistics

The sample comprised of 10,482 people (Fig. 1A). We performed a complete case analysis excluding those with any missing information. Wilcoxon test showed no significant differences (p=0.989) in PHQ–9 scores between the retained sample and the excluded cases (N = 923).

Table 1 summarizes the characteristics of the study population. On average, the PHQ–9 score was 4.883 (SD ± 4.941) and ranged from 0 to 27. In urban areas, the PHQ–9 was 5.074 (SD ± 5.047) and in rural areas, it was 4.480 (SD ± 4.683). The Kruskal-Wallis test showed a significant difference in depression levels between urban and rural areas (p<0.001) (Supplementary Table S1). The mean age was 44.617 years (SD ± 13.970). 52.4% were female, 73.4% were employed, 52.0% were married, and 44.0% were highly educated. The majority (67.8%) of participants lived in urban areas.

Average exposure to ALAN was 13.636 (SD = ±11.514) for 100 m residential buffers. Concentrations were comparable in magnitude for the 600 m buffer size. ALAN varied significantly

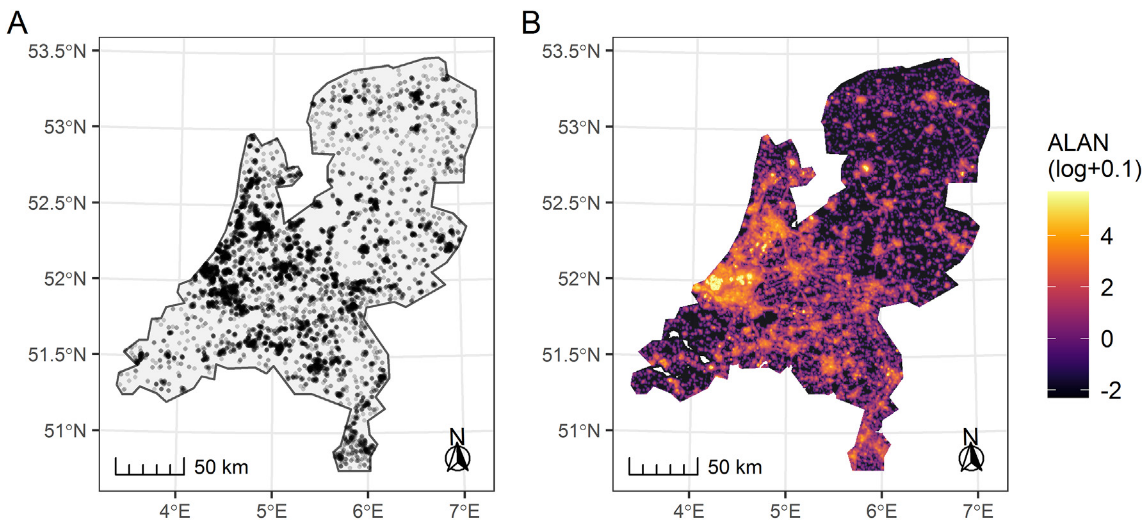

Fig. 1. (A) Residential locations of the study population ($N = 10{,}482$) For visualization purposes only, we added random noise with a mean of 1000 m and standard deviation (SD) of 2000 m to each location for privacy. (B) ALAN (in nW/cm^2/sr log-transformed +0.1) in the Netherlands. High ALAN pollution appears in the Amsterdam (52°22′N, 4°54′E) and the Delft, Rotterdam, and The Hague region (52°00′N, 4°50′E).

($p<0.001$) between urban ($\mu_{urban} = 17.551$, SD $\pm$ 11.742) and rural areas ($\mu = 5.374$, SD $\pm$ 4.558) (Supplementary Table S1). The Randstad area displayed particularly high levels of ALAN (Fig. 1). Fig. 2 shows that mean ALAN exposures increased with PHQ–9 scores. Spearman correlations between ALAN and the other exposures are summarized in Fig. S3. The Spearman correlation between ALAN and NO_2 was with 0.848 strong ($p<0.001$).

3.2. Regression models

With the largest GVIF of 2.651, there was no evidence for covariate multicollinearity. The comparison of the AIC scores of Model 1–4 indicated that the fully adjusted Model 3 performed best; there was no support of the inclusion of a soap film smother of people's address location (Model 4). With an adjusted R^2 of 0.109 and an explained deviance of 0.111, Model 3 had a moderate fit that varied little across buffer sizes. Person residuals revealed no violations, and there was also no residual spatial autocorrelation (Supplementary Fig. S5).

Estimated associations between PHQ–9 scores and outdoor exposure to ALAN are summarized in Fig. 3 (see Supplementary Table S3-S4 for numeric results). The magnitude of the associations was attenuated with increasing levels of adjustment. Model 3 using the 100 m buffers showed that people exposed to higher levels of ALAN in the 2nd to 5th quintile had higher PHQ–9 scores than people residing in neighborhoods that displayed the lowest levels of nightlight pollution (1st quintile), but there was no indication of an exposure-response relationship. The filly adjusted model with the 600 m buffers showed non-significant association between ALAN and PHQ–9 scores (Model 3).

Sensitivity analyses with 100 m buffers (Supplementary Table S5) did not show an exposure-response relationship between PHQ–9 scores and increasing levels of outdoor ALAN restricted to neighborhoods in urban ($N = 7112$; Model 5) or rural areas ($N = 3370$; Model 6). Replacing $PM_{2.5}$ with NO_2 (Model 7) attenuated risk estimates further. Estimates for Q2 were significant but those for the highest three exposure categories (Q3-Q5) did not reach statistical significance. Of other evaluated exposures, higher NO_2 concentrations translated into higher PHQ–9 scores, as did higher levels of neighborhood deprivation. Finally, refitting Model 3 with those people who lived at their residential location for at least one year ($N = 9492$) also attenuated risk estimates (Model 8). PHQ–9 scores were significantly higher for people in areas with moderate ALAN levels (Q2) but insignificant for those living in areas with high ALAN levels (Q3-Q5).

4. Discussion

4.1. Main findings

People around the world are increasingly exposed to nocturnal lighting. Our results, which are based on a representative sample of the Dutch population, partially supported the hypothesis that satellite-measured outdoor ALAN correlate with decreased mental health. We observed a statistically significant increase in depressive symptoms with increasing levels of outdoor ALAN in the immediate residential environment in unadjusted models. The association remained significant after adjusting for person-level and environmental correlates (e.g., $PM_{2.5}$, urbanicity, noise, land-use diversity, greenness, deprivation, social fragmentation). Adjusting for NO_2 rather than $PM_{2.5}$ showed a positive association for the second quintile but did not suggest an exposure-response relationship. This result suggested that associations between mental health and ALAN might be substantially confounded by NO_2. This is not unexpected because the pattern of the NO_2 concentrations (as did ALAN) aligned well with the extent of urban environments, while $PM_{2.5}$ concentrations are higher along major roads (Fig. S6).

4.2. Other available evidence

We are only aware of a limited number of similar studies addressing light exposure effects on mental health. Our estimates for outdoor ALAN were similar to those observed in another cross-sectional study of 113,119 South Koreans aged 20–59 years. In the current study, the odd ratios for depressive symptoms were higher for people exposed to higher ALAN levels than those reported for Korea (Min and Min, 2018). However, in the Korean study, light pollution data were captured with a less accurate sensor from the Defense Meteorological Satellite Program (Levin et al., 2020; Miller et al., 2013), aggregated for 232 districts rather than calculated by individual residential addresses, and adjusted for $PM_{2.5}$ but not NO_2.

It is important to note differences in previous research and ours, limiting their comparability. The Korean study assumed—like we have done here and have done previously (Portnov et al., 2016)—that artificial light from the outside reaches people inside. This assumption has been questioned by contrasting remote-sensing based outdoor ALAN assessments with in situ bedroom measurements of illuminance among 256 Dutch children (Huss et al., 2019). While correlations showed minor

Table 1
Characteristics of the study population.

	Total	ALAN					p-value
		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	
		[0–4.63] (N = 2135)	[4.63–8.49] (N = 2133)	[8.49–13.3] (N = 2101)	[13.3–21.1] (N = 2068)	[21.1–97.4] (N = 2045)	
PHQ–9 score [Mean (SD)]	4.883 (4.941)	4.223 (4.364)	4.726 (4.951)	4.811 (4.953)	5.144 (5.042)	5.545 (5.274)	<0.001
Gender (%): Male	47.6	47.3	46.6	46.8	50.6	46.8	0.050
Female	52.4	52.7	53.4	53.2	49.4	53.2	
Age [Mean (SD)]	44.617 (13.970)	46.059 (13.977)	45.741 (13.592)	45.424 (13.656)	43.993 (14.069)	41.739 (14.122)	<0.001
Employment status (%): Employed	73.4	72.6	75.1	73.5	73.4	72.2	0.038
Unemployed	4.9	4.0	4.9	4.6	5.1	5.9	
Non-working	19.6	21.4	17.4	19.7	19.7	19.9	
Other	2.1	2.1	2.6	2.1	1.8	2.1	
Marital status (%): Married	52.0	60.1	58.6	56.2	48.2	36.0	<0.001
Separated	8.7	8.0	8.1	9.3	9.8	8.6	
Widowed	1.5	1.7	1.2	1.5	1.8	1.3	
Unmarried	37.8	30.2	32.0	33.0	40.2	54.2	
Education level (%): Low	19.9	22.0	20.8	21.0	20.1	15.6	<0.001
Mid	36.1	40.4	39.1	35.6	34.9	30.0	
High	44.0	37.7	40.1	43.3	45.0	54.4	
Household type (%): Other	16.8	9.9	11.3	14.1	20.3	29.2	<0.001
Couple without child	30.9	32.2	31.0	29.4	29.6	32.1	
Couple with child	46.0	53.4	51.3	49.5	43.0	32.2	
Single parent	6.3	4.4	6.3	7.0	7.1	6.5	
Ethnicity (%): Dutch	86.7	94.1	91.3	86.7	83.5	77.3	<0.001
Western	7.8	4.9	6.1	8.7	9.1	10.5	
Non-western	5.5	1.0	2.6	4.6	7.4	12.2	
Household income (%): Very low	10.0	5.5	7.5	8.9	10.8	17.5	<0.001
Low	10.7	9.2	11.1	10.0	11.5	11.8	
Middle	19.2	20.9	20.4	19.5	18.8	16.3	
High	26.2	28.7	28.5	27.4	25.0	21.1	
Very high	33.9	35.7	32.5	34.2	33.8	33.2	
Population density (100 m) [Mean (SD)]	216.953 (150.259)	95.235 (69.635)	170.843 (77.772)	204.079 (94.404)	251.782 (110.869)	370.131 (200.617)	<0.001
ALAN (100 m) [Mean (SD)]	13.636 (11.514)	2.473 (1.334)	6.575 (1.117)	10.746 (1.406)	16.833 (2.182)	32.392 (10.802)	<0.001
Noise (100 m) [Mean (SD)]	55.755 (5.228)	51.950 (4.925)	54.099 (4.280)	56.027 (4.277)	57.599 (4.430)	59.309 (4.793)	<0.001
Shannon index of building usage (100 m) [Mean (SD)]	0.227 (0.252)	0.172 (0.239)	0.190 (0.238)	0.215 (0.244)	0.252 (0.250)	0.309 (0.263)	<0.001
Social fragmentation (100 m) [Mean (SD)]	−0.033 (2.464)	−1.126 (1.998)	−0.803 (1.762)	−0.506 (1.913)	0.310 (2.290)	2.051 (2.845)	<0.001
Deprivation (100 m) [Mean (SD)]	−0.040 (2.142)	−0.484 (2.215)	−0.284 (2.438)	−0.109 (1.819)	0.122 (1.954)	0.587 (2.062)	<0.001
$PM_{2.5}$ (100 m) [Mean (SD)]	16.609 (0.694)	16.231 (0.714)	16.494 (0.652)	16.627 (0.622)	16.757 (0.610)	16.954 (0.645)	<0.001
NO_2 (100 m) [Mean (SD)]	24.992 (6.712)	17.509 (3.240)	21.724 (2.936)	24.694 (3.369)	28.035 (3.817)	33.439 (5.845)	<0.001
Greenness (100 m) [Mean (SD)]	28.944 (19.220)	43.456 (22.467)	30.297 (16.773)	26.448 (14.802)	24.284 (14.899)	19.661 (16.961)	<0.001
Population density (600 m) [Mean (SD)]	4744.872 (3665.098)	1368.652 (1046.033)	3238.805 (1300.149)	4450.541 (1661.410)	5858.917 (2292.177)	9016.372 (4894.143)	<0.001
ALAN (600 m) [Mean (SD)]	13.438 (11.517)	2.348 (1.301)	6.344 (1.252)	10.558 (1.704)	16.723 (2.480)	32.055 (10.973)	<0.001
Noise (600 m) [Mean (SD)]	56.455 (4.645)	51.434 (3.820)	54.904 (3.390)	57.089 (3.230)	58.736 (3.254)	60.359 (3.499)	<0.001
Shannon index of building usage (600 m) [Mean (SD)]	0.414 (0.191)	0.374 (0.199)	0.375 (0.177)	0.406 (0.184)	0.444 (0.180)	0.476 (0.193)	<0.001
Social fragmentation (600 m) [Mean (SD)]	−0.005 (2.527)	−1.542 (1.787)	−1.083 (1.477)	−0.464 (1.769)	0.481 (2.166)	2.706 (2.771)	<0.001
Deprivation (600 m) [Mean (SD)]	−0.003 (2.264)	−0.861 (2.166)	−0.460 (1.851)	−0.053 (2.083)	0.301 (2.209)	1.112 (2.468)	<0.001
$PM_{2.5}$ (600 m) [Mean (SD)]	16.657 (0.653)	16.236 (0.687)	16.542 (0.639)	16.691 (0.588)	16.825 (0.549)	17.011 (0.505)	<0.001
NO_2 (600 m) [Mean (SD)]	24.709 (6.791)	16.901 (3.170)	21.320 (2.900)	24.463 (3.252)	27.975 (3.821)	33.345 (5.519)	<0.001
Greenness (600 m) [Mean (SD)]	43.929 (19.301)	69.118 (15.213)	49.640 (11.820)	39.834 (10.948)	33.453 (10.690)	26.473 (12.423)	<0.001

Note. Chi^2 tests were used for categorical variables and Kruskal–Wallis tests for continuous ones to assess differences across quintiles.

to no agreement between both exposure assessments, outdoor ALAN levels were positively correlated with air pollution, which suggests VIIRS data may be a weak proxy for actual ALAN exposure. Our findings support the notion of air pollution as a highly correlated exposure with outdoor ALAN that should likely be accounted for in epidemiological studies. Furthermore, a positive cross-sectional association was reported for a small sample of 516 elderly in the Kansai Region, Japan, (Obayashi et al., 2013) and reinforced through longitudinal evidence in a follow-up study using bedroom light measurements (Obayashi et al., 2018). This suggests that while bedroom-ALAN exposure may degrade mental health, evaluating associations using satellite-measured outdoor ALAN may produce biased results in studies that examine associations between light at night and depression.

Our findings that different air pollutants correlate differently in magnitude with depressive symptoms is in line with previous studies (Klompmaker et al., 2019; Zijlema et al., 2016). A meta-analysis of 22 studies from 10 countries showed no associations of long-term $PM_{2.5}$ and NO_2 with depression (Fan et al., 2020), another meta-analysis came to a different conclusion for $PM_{2.5}$ (Braithwaite et al., 2019). Our null findings of $PM_{2.5}$-depressive symptoms associations confirm Dutch results in a multi-site European cohort study (Zijlema et al., 2016). Similar to our results, a positive association between NO_2 and depressive symptoms was reported in a cross-sectional study from Barcelona, Spain (Vert et al., 2017). Despite ALAN turned out to be insignificant when adjusting for NO_2, we would like to stress that this result does not necessarily refute that true associations between ALAN and mental illness exist, since mechanistic research already explains such an association.

4.3. Potential mechanisms

To explain the neurobiological mechanisms of how ALAN may contribute to mood disorders, some potential pathways have been put

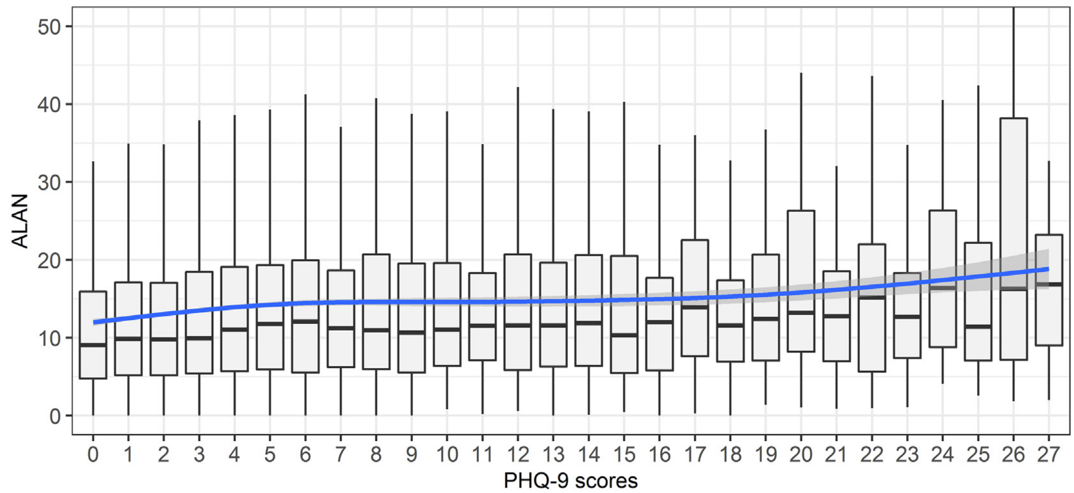

Fig. 2. Exposure to ALAN by PHQ–9 scores in the Netherlands. Boxplots were based on 100 m buffers (outliers not shown). 600 m buffers showed similar patterns. The superimposed regression line based on a GAM suggests an increase in ALAN exposure with increasing PHQ–9 scores.

forth (Haim and Zubidat, 2015; Lambert et al., 2015; Bedrosian and Nelson, 2013). A disruption of circadian rhythmicity seems central for mood disorders including depression (Lyall et al., 2018), while experimental studies on mice and hamsters suggested that abnormal light cycles lead to depression-like behaviors (Bedrosian et al., 2013; LeGates et al., 2012; Fonken and Nelson, 2013).

Similar pathways are plausible for humans' mental health, since people also follow circadian rhythms and sleep-wake cycles. It is speculated that disruptions due to alternations in the day-lengths by means of irregular light likely affects people's mood (LeGates et al., 2012). Here, the blue wavelengths that are strongly emitted in the outdoor light bulbs that are increasing used because of their high-efficiency status—these being light-emitting diodes (LEDs)—are of particular concern (Bierman, 2012). Blue wavelengths at night can suppress melatonin levels and their production (Haim and Zubidat, 2015), and melatonin exerts major control over sleep-wake-cycles. When ALAN exposures are ill-timed or constant, biological rhythms can be desynchronized and mood disorders exacerbated.

There are tenable mechanisms explaining how exposure to airborne pollutants have adverse neurophysiological effects (Buoli et al., 2018). Biological pathways include that fine particulate matter may cause environmentally induced neuroinflammatory and autoimmune responses (Block and Calderón-Garcidueñas, 2009; van den Bosch and Meyer-Lindenberg, 2019). Studies with mice exposed to $PM_{2.5}$ showed, for example, pronounced depressive-like responses compared to those exposed to filtered air (Fonken et al., 2011). Similar mechanisms via neuroinflammation are likely to be at play in the pathogenesis of depression in humans (Buoli et al., 2018).

4.4. Strengths and limitatations

A strength is the representative number of participants enriched with person-level register and environmental data. Due to our large sample size, the results were well-powered. An analytical novelty is, unlike earlier studies (James et al., 2017; Min and Min, 2018; Portnov et al., 2016), our adjustment for potentially unmeasured factors related to shared exposures among respondents living close together. This is an issue that may have induced a bias had it been ignored (Wood, 2017). Another strength is that we controlled for a variety of factors describing both the physical and social environment on an address level rather

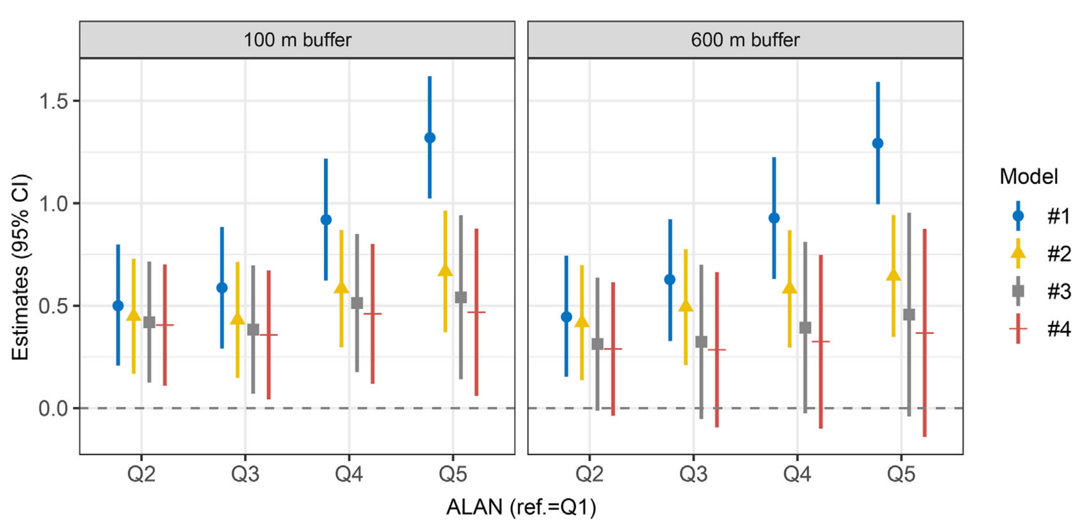

Fig. 3. Associations between ALAN quintiles (Q) at the place of residence and PHQ–9 scores across buffer sizes together with 95% confidence intervals (CI). Effects were estimated through GAMs with different adjustment levels. Model 1 was unadjusted, Model 2 was adjusted for person-level characteristics (i.e., gender, age, marital status, employment, education, household type, household income, and ethnicity), Model 3 was additionally adjusted for area-level covariates (i.e., Shannon index of building usage, $PM_{2.5}$, noise, population density, deprivation, social fragmentation, and greenness), and Model 4 additionally included a soap film smoother of the respondents' address coordinates. AIC scores were lowest for Model 3 with the 100 m buffer.

than on the level of administrative units (e.g., postal codes). No previous ALAN study has incorporated objectively measured area-level social aspects, to the best of our knowledge.

Notwithstanding these strengths, this study had limitations. Our analyses were based on self-reported depressive symptoms, which may have biased the regression estimates. The survey response rate was moderate and some selection bias cannot be ruled out. Our survey and ALAN data were not perfectly aligned which may have led to contextual uncertainties in exposure assessments. To assess personal or bedroom ALAN exposure, information on indoor light conditions or bedroom measurements to collect night light data with luminance meters would have been necessary, but this step would have been labor-intensive and time-consuming with such a large sample (Hänel et al., 2018). Although our objective environmental assessments are not prone to subjective evaluations and recall bias, we cannot rule out that perceptions of residential environments differ. Another consideration is that we could not rule out unmeasured and residual confounding. Data on shift-working and sleep quality—both of which are correlated with depressive symptoms—were not available (Bedrosian and Nelson, 2013). Our cross-sectional findings are also vulnerable to reverse causality – a limitation that applies to many studies (Min and Min, 2018; Portnov et al., 2016). Lastly, we cannot assume that residential self-selection has not occurred. People without depressive symptoms may choose to live in neighborhoods with less light or other traffic-related pollution. It is therefore crucial to perform studies with more robust designs such as longitudinal studies during natural experiments and cohorts with follow-up data collection.

5. Conclusions

In this comprehensive national study, we observed a positive association between exposure to outdoor ALAN within the immediate residential environment and depressive symptoms. The association persisted after comprehensive adjustments for other exposures including $PM_{2.5}$, urbanicity, noise, land-use diversity, greenness, deprivation, and social fragmentation. However, outdoor ALAN was highly correlated with traffic-related air pollution, especially NO_2, which has been reported to affect mental health. Accounting for NO_2 exposure suggested that air pollution rather than outdoor ALAN may increase PHQ–9 scores. Our findings support the notion that future evaluations of health effects based on satellite-measured outdoor ALAN should account for traffic-related air pollutants (i.e., NO_2). Because ALAN represents a preventable and modifiable exposure, further research on a possible association between ALAN and several health endpoints remains relevant.

CRediT authorship contribution statement

Marco Helbich: Conceptualization, Methodology, Formal analysis, Data curation, Resources, Writing - original draft, Visualization, Project administration, Funding acquisition. **Matthew H.E.M. Browning:** Conceptualization, Writing - review & editing. **Anke Huss:** Conceptualization, Writing - review & editing.

Declaration of competing interest

The authors have no conflict of interest to declare.

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Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.140914.

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