Health & Place 95 (2025) 103504

Contents lists available at ScienceDirect

Health and Place

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

Heterogeneous effects of artificial light at night on sleep and mental health: 2SLS augmented geospatial data modeling and geo-correlation analysis

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ARTICLE INFO

Keywords:
Public health
Artificial light at night (ALAN)
Two-stage least squares (2SLS)
Health geography
Remote sensing

ABSTRACT

Rapid urbanization has led to a significant increase in artificial light at night (ALAN), raising concerns about its potential adverse effects on human health. Yet, evidence on the relationship between ALAN, sleep, and mental health remains limited. In this study, we utilized the Extended Time-Series of Global NPP-VIIRS-like Nighttime Light Data and population distribution maps to estimate population-weighted ALAN at the census tract level across 500 major U.S. cities from 2013 to 2019. We also obtained the prevalence of frequent mental distress and short sleep duration from the SDOH database. A Two-Stage Least Squares (2SLS) model was applied to investigate the causal relationships between ALAN, sleep, and mental health, as well as heterogeneity across differing educational and urbanization levels. The findings revealed that: (1) Population-weighted ALAN was significantly associated with both sleep and mental health, with a ten-fold increase in O-ALAN corresponding to an 8.05 % ($\pm$0.04 %) rise in mental distress prevalence and a 4.99 % ($\pm$0.07 %) increase in short sleep duration prevalence; (2) higher education levels intensified the negative impact of ALAN on mental health but mitigated its effect on sleep; and (3) higher urbanization levels amplified ALAN's adverse effects on both sleep and mental health. This study is the first to examine the relationship between population-weighted ALAN and sleep and mental health outcomes while accounting for economic endogeneity, offering a comprehensive view of ALAN's impact on health.

1. Introduction

Over the past few decades, rapid urbanization and industrialization have significantly increased artificial light at night (ALAN) in global cities (Cauwels et al., 2014). The introduction of artificial lighting has altered the spectrum, intensity, and timing of light. Previous studies reported that nearly 80 % of the U.S. population lives in areas where the natural night sky is no longer visible, and about 40 % reside in regions where artificial light hinders proper nocturnal adaptation of the human eyes (Falchi et al., 2016). Furthermore, outdoor ALAN continues to expand, with some cities experiencing annual increases in light pollution ranging from 5 % to 20 % during the latter half of the 20th century (Hölker et al., 2010). ALAN has become a ubiquitous environmental pollutant in modern society.

Unlike other pollutants, ALAN does not pose direct toxic effects. However, emerging evidence suggests that ALAN exerts multifaceted impacts on human health through complex pathways. A recent systematic evidence map categorizes these impacts into three domains: (1) direct physiological effects (e.g., circadian disruption, melatonin suppression), (2) psychological consequences (e.g., depression, anxiety), and (3) social determinants of health, including neighborhood safety and environmental justice (Liu et al., 2023). Additionally, using ALAN in certain ways may also lead to opposite health effects. For example, short exposure to ALAN may help phase adaptation (Chinoy et al., 2016) and reduce work-related risks (Figueiro et al., 2016). The complexity and diversity of these issues have kept growing with more studies in the last two decades. Among these, the role of ALAN in mental health is a domain accounting for 23.9 % of recent ALAN-health research (Liu et al., 2023).

Indoor ALAN has been shown to acutely disrupt sleep by suppressing melatonin production and delaying circadian rhythms (Obayashi et al., 2014). The psychological consequences due to ALAN are another area of

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https://doi.org/10.1016/j.healthplace.2025.103504
Received 25 November 2024; Received in revised form 9 June 2025; Accepted 19 June 2025

interest. Melatonin suppression caused by ALAN exposure is believed to disturb circadian and endocrine hormonal balance, negatively affecting mental health (Nelson and Chbeir, 2018). Additionally, light exposure can directly influence mood, independent of circadian and sleep changes (Fernandez et al., 2018). For instance, it can affect mood by regulating the secretion of neurotransmitters like serotonin (Blume et al., 2019). Additionally, ALAN exposure has also been associated with the dysregulation of the immune system, which can modulate brain functions, including cognition and emotion (Navara and Nelson, 2007). Previous studies have suggested that ALAN can significantly impact public health, with effects becoming more pronounced as the extent and intensity of artificial lighting increase (Kyba et al., 2017). It is postulated that the adverse effects of ALAN are not confined to indoor lighting; outdoor ALAN (O-ALAN) in urban environments may also affect human health. Although the intensity of O-ALAN is generally lower, even dim light comparable to candlelight can influence the human circadian rhythm, highlighting its potential to affect human health (Duffy and Wright, 2005). O-ALAN can also impact indoor environments when curtains or shades fail to block outdoor light effectively (Stevens, 2011). Additionally, O-ALAN can expose those who are outdoors late at night to higher light levels. Since the near-inevitability of exposure to O-ALAN affects almost everyone in illuminated areas, it poses great concerns for public health, which, however, has not been well addressed yet. Thus, the major objective of this study is to evaluate O-ALAN as a form of pollution to investigate its association and potential causative relationships with human health, particularly in terms of sleep and mental health.

The existing cross-sectional epidemiological studies on the relationship between O-ALAN and sleep consistently provided evidence of O-ALAN's detrimental impact on sleep. For instance, a study found that individuals living in areas with high O-ALAN levels were more likely to report shorter sleep durations in the US (Xiao et al., 2020). Research also determined a nonlinear relationship between O-ALAN exposure and sleep parameters such as duration and quality (Ohayon and Milesi, 2016; Paksarian et al., 2020), and factors like low income and noise may exacerbate O-ALAN's impact on sleep (Gabinet and Portnov, 2021). Additionally, a study from South Korea found a statistically significant association between O-ALAN exposure and the use of sleep-inducing medications (J.-Y. Min and Min, 2018). The overall body of evidence suggests that O-ALAN could contribute to sleep deprivation. Even few epidemiological studies have examined the relationship between O-ALAN and mental health, and the findings remain inconsistent (Wang et al., 2023). A study from South Korea found that adults living in areas with higher levels of light pollution were more likely to experience depressive symptoms (J. Min and Min, 2018). Similarly, a positive correlation between O-ALAN exposure and feelings of low mood, lack of enthusiasm, and fatigue was revealed in a sample from the United Kingdom (Liao et al., 2023). In contrast, a study of the Dutch population found that while depressive symptoms increased with rising levels of O-ALAN, the association disappeared after adjusting for nitrogen dioxide (NO_2) (Helbich et al., 2020). Another study indicated a weak link between O-ALAN exposure and poor mental health in rural U.S. areas affected by shale gas development (Boslett et al., 2021). Given the current inconclusive evidence, it is imperative to identify possible relationships between O-ALAN and mental health (Bozejko et al., 2023).

Most of these studies have been conducted on small-scale and relatively homogeneous populations or under controlled laboratory conditions. Consequently, the generalizability of the observed relationships and their applicability to real-world settings remain uncertain. Given the diversity in human lifestyles and behavioral patterns shaped by geographic, climatic, cultural, and social contexts, a comprehensive understanding of how O-ALAN affects human health requires evidence from both medical and social sciences. Research employing panel data and methods better suited for testing causal relationships is particularly needed (Wang et al., 2023). Ecological studies, in particular, can capture populations that cohort studies may not fully represent. In this context, ecological research may offer stronger epidemiological evidence than small-sample cohort studies (Bozejko et al., 2023). Existing ecological studies use average pixel values of nighttime light in an administrative unit as a proxy for O-ALAN level (Paksarian et al., 2020; Patel, 2019). However, significant variation in light intensity and population density within these units can lead to considerable misestimation of actual population exposure. Additionally, some studies have found different associations between O-ALAN and sleep deprivation in areas with varying income levels (Xiao et al., 2020), yet no comparable analyses have been conducted across regions with differing educational attainment. Furthermore, endogeneity may arise from unmeasured factors that simultaneously influence both O-ALAN and health outcomes. For example, socio-economic conditions could drive both light pollution and other determinants of sleep and mental health. To address the endogeneity stemming from such omitted variables, it is appropriate to identify instrumental variables that directly associate and even influence nighttime light, which may further affect human health.

Particularly, in this study, we aim to quantify the potential effects of O-ALAN, as a form of pollution, on sleep and mental health at the census tract level. To achieve that, we calculated population-weighted O-ALAN exposure for census tracts in the 500 largest cities in the contiguous US from 2013 to 2019. To account for endogeneity related to socio-economic conditions, we employed a Two-Stage Least Squares (2SLS) instrumental variable approach to examine the relationship between regional O-ALAN exposure and the prevalence of insufficient sleep and poor mental health. The major contributions of this study include: (i) determining whether O-ALAN at the census tract level is associated with insufficient sleep and poor mental health; and (ii) assessing whether the relationship between O-ALAN and these health outcomes varies according to other social or environmental factors, such as differences in educational attainment and urbanization levels.

2. Methods

2.1. Data source

We utilized an Extended Time-Series of Global NPP-VIIRS-like Nighttime Light Data to compute population-weighted O-ALAN (Chen et al., 2020). This dataset provides annual composites of NPP-VIIRS-like nighttime light images, from 2000 to 2023, at a 500-m resolution, with the unit of $nW/cm^2/sr$. It employs a self-coder-based cross-sensor (DMSP-OLS and NPP-VIIRS) nighttime light data calibration scheme, and has the same parameter attributes and similarity to the NPP-VIIRS nighttime light data. It contains annual composites made after excluding the outer quarters of the satellite swath, sun and moon luminance, glare, clouds, atmospheric lightning, and ephemeral events such as fires, and represents the relative levels of nighttime illumination at the ground level. The dataset was validated using 150,000 randomly selected pixels and 40,000 cities, demonstrating a nearly 1:1 relationship with the original NPP-VIIRS data, with pixel-level and city-level R^2 equaling 0.87 and 0.95, respectively.

We also obtained 100-m resolution population distribution grid maps from WorldPop (www.worldpop.org), which provides high-resolution population estimates based on a combination of census data, satellite imagery, and various geospatial datasets. The boundaries for census tracts were sourced from the US Census Bureau's TIGER/LINE database (https://tigerweb.geo.census.gov/). Since administrative boundaries in the US underwent adjustments during the study period, we carefully processed census tracts that experienced boundary changes to ensure consistency throughout the analysis.

Health conditions (i.e., prevalence of frequent mental distress and short sleep duration) and some socio-economic covariates were obtained from the PLACES dataset (https://www.cdc.gov/places/index.html). This dataset is an expansion of the original 500 Cities Project, which provided both city-level and census tract-level estimates of chronic disease risk factors and health outcomes for the largest 500 cities in the

US. PLACES used a multilevel regression and poststratification (MRP) method to generate estimates using the Behavioral Risk Factor Surveillance System (BRFSS) data (http://www.cdc.gov/brfss/technical_infodata/surveydata.htm), which is an annual telephone health survey for tracking health conditions and risk behaviors of the adult population in the US. Thus, the PLACES dataset offers comprehensive small-area estimates across the urban-rural spectrum. Both internal and external validation studies show strong to moderate correlations between model-based and direct survey estimates at various levels. We also utilized the Social Determinants of Health (SDOH) dataset (https://www.ahrq.gov/sdoh/data-analytics/sdoh-data.html) to obtain several covariates at the census tract level. This dataset is curated by the Agency for Healthcare Research and Quality (AHRQ) and integrates data from various federal sources, including the Centers for Disease Control and Prevention (CDC) and the American Community Survey (ACS). This dataset provides detailed information across five key domains: social context, economic context, education, physical infrastructure, and healthcare context.

We used a satellite-derived $PM_{2.5}$ concentration map with a 1-km resolution to estimate $PM_{2.5}$ concentrations (Shen et al., 2024). This dataset enhanced global $PM_{2.5}$ distribution estimates by optimizing a convolutional neural network with data from satellite, simulation, and monitoring sources. It demonstrates strong consistency with global observations, even under extreme conditions (e.g., 1 % for training, R^2 equaling 0.73). NO_2 concentration maps with the same spatial resolution were obtained from satellite imagery using a land-use regression model (Anenberg et al., 2022). Temperature data was sourced from the National Tibetan Plateau Data Center, providing monthly land-surface temperatures at a 5-km resolution (Ma Yaoming and Chen, 2021). For subgroup analysis, we used the 2013 Urban-Rural Classification Scheme for counties, provided by the National Center for Health Statistics (NCHS). This scheme classified counties into six categories: large central metro, large fringe metro, medium metro, small metro, micropolitan, and noncore from most urban to most rural. Since the classification is county-based, all census tracts within a county share the same urban-rural category. The main technical lines of the article are shown in Fig. 1.

2.2. Population-weighted O-ALAN measurement

We defined population-weighted O-ALAN of each census tract by assigning a population-based weight to the nighttime light value of each pixel and then aggregating these weighted values within the census tract. The specific calculation process is outlined as follows. First, we resampled the gridded population distribution map to ensure alignment with the nighttime light data, allowing us to determine continuous-scale O-ALAN levels. Second, we assigned population-based weights to the O-ALAN pixels and aggregated them by administrative units. Each grid was weighted according to its proportion of the census tract's total population. The weighted ALAN values were then summed across the entire administrative unit to derive the population-weighted ALAN, calculated in Equation (1):

$$NTL_w = \frac{\sum_{i=1}^{n} NTL_i \cdot Pop_i}{\sum_{i=1}^{n} Pop_i} \quad (1)$$

where NTL_w is the population-weighted of a census tract, n is the total number of pixels in the administrative unit, and NTL_i and Pop_i are the O-ALAN value and the population of the pixel i, respectively.

2.3. Sleep and mental health outcomes

After eliminating a small portion of records with missing values in the PLACES from 2013 to 2019, records in 26,678 census tracts were maintained. We examined two variables closely related to human conditions: frequent mental distress and short sleep duration. Specifically, frequent mental distress comes from self-reports that demonstrate unwell mental conditions (i.e., stress, depression, and problems with emotions) lasting for at least 14 days during the past 30 days. Short sleep duration, also coming from self-reports, presents sleep duration shorter than 7 h during a 24-h period. Both variables are estimated as the age-adjusted prevalence in census tracts.

2.4. Covariates

Population heterogeneity – including factors such as age, race, health risk behaviors, and employment status, as well as environmental factors like air pollutants and temperature - can influence sleep and mental health outcomes (Gabinet and Portnov, 2021; Helbich et al., 2020; Hu et al., 2022; Koo et al., 2016; Zhu et al., 2024). Although gender is often considered in health studies, it has not been found to impact sleep or mental health in the context of O-ALAN exposure (Paksarian et al.,

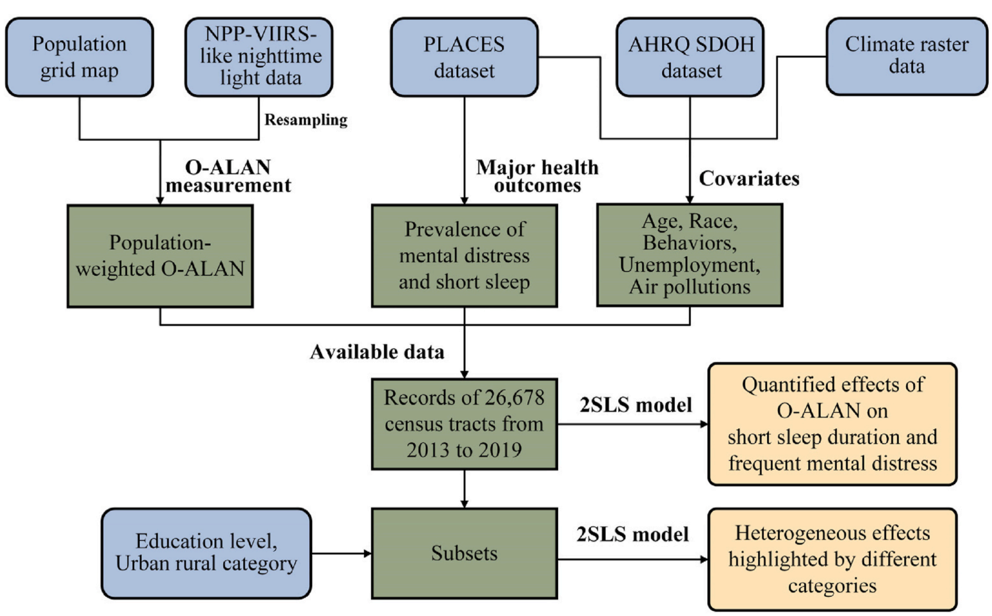

Fig. 1. Main data source and technical lines of this article. Blue boxes are raw data, green boxes are processed records, and yellow boxes are the outcome.

2020), which was also observed in our preliminary analyses. Air pollution, particularly $PM_{2.5}$ and NO_2, has been linked to sleep and mental health outcomes. Notably, Helbich et al. (2020) found that the association between O-ALAN and depression remained significant after adjusting for $PM_{2.5}$, but became non-significant after adjusting for NO_2. Therefore, we adjusted for both $PM_{2.5}$ and NO_2 separately in our analysis.

From the SDOH dataset, we selected the following variables at the census tract level: the percentage of population ages 65 and over, the percentage of population reporting Black or African American race alone, the percentage of population with a disability, and the percentage of civilian labor force that is unemployed (ages 16 and over). Due to data availability constraints and the need for analytical consistency, binge drinking and smoking were included as covariates to partially account for behavioral health influences. We obtained the prevalence of binge drinking, as a health risk behavior covariate, from the PLACES dataset mentioned above. It was identified by self-reports that they had five or more drinks for men and four or more for women on one occasion during the previous 30 days.

Unlike ALAN, which exhibits high spatial heterogeneity, climate data, including air pollutants and temperature, are influenced by atmospheric mixing and regional weather patterns, leading to relatively uniform distributions within census tracts. The population-weighted and average air pollutant concentrations and temperature revealed negligible differences (<5 %). Thus, we measured the mean $PM_{2.5}$, NO_2 concentrations, and the mean temperature by simply averaging pixel values within each census tract using raster data. Other environmental factors were not included due to the lack of consistent and high-resolution data across all census tracts and years.

2.5. Analysis

We calculated descriptive statistics for the entire sample, and then separately for those census tracts below and above the median of population-weighted O-ALAN. We compared the descriptive statistics of these two groups using t-tests for differences in means and chi-squared tests in proportions, and examined the spatial distribution of the population-weighted O-ALAN and the prevalence of the two health risk conditions. Additionally, non-parametric Spearman correlation coefficients were used to assess bivariate associations.

Given that ALAN intensity follows a skewed distribution, with many low-exposure areas and a few highly illuminated regions, we applied logarithmic transformations to the population-weighted O-ALAN in the model (Liu et al., 2024). The logarithmic transformation mitigates the skewness of the distribution of the outdoor ALAN exposure and converts it into a normal distribution (Benoit, 2011). We applied the 2SLS model, using the prevalence of frequent mental distress and short sleep duration as the dependent variables, with the natural logarithm of population-weighted O-ALAN as the key independent variable. The 2SLS model is well-suited for addressing endogeneity concerns when explanatory variables are correlated with the error term, leading to biased and inconsistent coefficient estimates in standard regressions and compromising causal inference. The 2SLS mitigates endogeneity by utilizing an instrumental variable (IV), which is correlated with the endogenous explanatory variable but uncorrelated with the error term. Under certain conditions, this instrument isolates variation in the regressor that is exogenous, allowing for an unbiased estimate of the coefficient of interest.

The 2SLS involves two key steps: (i) in the first stage regression, the endogenous explanatory variable is regressed on the instrumental variable, yielding predicted values purged of endogeneity, and (ii) in the second stage regression, the predicted values are then used as explanatory variables in the original regression. The coefficients estimated in this second stage reflect the causative relationships, free from the bias introduced by endogeneity. We specifically used the percentage of population living below 1.37 times the poverty threshold (sourced from the AHRQ SDOH database) as an IV for population-weighted O-ALAN when estimating the relationship between health outcomes and O-ALAN. This IV is correlated with changes in ALAN levels and other related factors, but is not directly associated with the prevalence of health risk conditions. We further included the year effects, mitigating potential confounding influences associated with time. The developed 2SLS model involves the estimation as presented in Equations (2) and (3):

$$Log_{10}ALAN_w = \gamma_0 + \gamma_1 PP + \gamma_x X + \varepsilon_1 + \delta \tag{2}$$

$$Prevalence = \beta_0 + \beta_1\, Log_{10}\widehat{ALAN}_w + \beta_x X + \varepsilon_2 + \delta \tag{3}$$

where $ALAN_w$ represents the population-weighted O-ALAN of census tracts, γ_0 is the intercept term, γ_1 is the coefficient for the instrumental variable, PP is the percentage of population below 1.37 times the poverty threshold, X is a set of covariates, γ_x is a vector of coefficients associated with the covariates, and ε_1 is the error term in the first stage regression. δ presents the year effects. *Prevalence* is the prevalence of health risk conditions (frequent mental distress and short sleep duration), β_0 is the intercept term of the second stage regression, β_1 is the coefficient for the primary explanatory variable, $\widehat{ALAN}_w$ is the predicted values from the first stage, which is free from endogeneity bias, β_x is a vector of coefficients associated with the covariates, and ε_2 is the error term in the second stage regression.

To explore the different impacts of O-ALAN on human health in census tracts of different urbanicity and education levels, we performed the 2SLS model on subsets categorized by various urban-rural classifications. We also divided the census tract samples into four quartiles based on the educational attainment of the population, and analyzed each subgroup separately. The education levels of census tracts are presented by the following variables from the AHRQ SDOH database: the percentage of population with a master's or professional school degree or doctorate, bachelor's degree, college or associate's degree, any postsecondary education, only high school diploma, and less than high school education. We classified census tracts into four quartiles based on each educational attainment level. For instance, when stratifying using bachelor's degrees, Q4 represents the top 25 % of census tracts with the highest percentage of bachelor's degree holders, while Q1 represents the bottom 25 % with the lowest percentage.

3. Results

3.1. Descriptive statistics and spatial patterns

Our sample included 26,678 census tracts of 500 large cities in the contiguous US with complete data available for all variables (Table 1). During the study period, the mean population-weighted O-ALAN of these census tracts was 35.47 nW/cm^2sr. Census tracts with higher O-ALAN level (i.e., above the median for the O-ALAN level) had statistically significantly higher prevalence of frequent mental distress (14.68 % in higher O-ALAN areas, and 13.2 % in lower O-ALAN areas) and short sleep duration (38.12 % in higher O-ALAN areas, and 35.1 % in lower O-ALAN areas). These tracts also had higher unemployment rates, a larger percentage of the population in poverty, and lower per capita incomes. Additionally, they had a larger proportion of individuals with higher education degrees (master's, bachelor's, and associate degrees) and fewer individuals with lower levels of education (high school or less).

All these differences were statistically significant. The population-weighted O-ALAN showed substantial variations across census tracts, while the prevalence of frequent mental distress and short sleep duration exhibited much smoother variations (Table 1 and Fig. 2). In the spatial analysis, high O-ALAN value, high prevalence of frequent mental distress, and high prevalence of short sleep duration shared a similar geographic distribution (Fig. 3). The map highlights that areas with higher O-ALAN and prevalence are at the heart of major metropolitan

Table 1
Descriptive Statistics: Census tracts of 500 large cities in the US, 2013–2019.

Variable	Full Sample	Above-Median ALAN	Below-Median ALAN	
	Mean (SD)	Mean (SD)	Mean (SD)	*p*
Population-weighted ALAN, nW/cm^{2}sr	35.47 (53.21)	55.97 (69.13)	14.97 (6.63)	<0.001
Health Outcome				
Frequent mental distress, %	13.94 (3.41)	14.68 (3.52)	13.20 (3.13)	<0.001
Short sleep duration, %	36.61 (5.81)	38.12 (5.86)	35.10 (5.35)	<0.001
Age				
<15, %	19.10 (6.38)	18.63 (7.04)	19.57 (5.60)	<0.001
>65, %	12.61 (6.77)	11.76 (6.36)	13.46 (7.05)	<0.001
Race/Ethic				
Asian, %	7.15 (10.63)	7.18 (10.87)	7.12 (10.39)	0.62
Black, %	20.54 (26.61)	25.61 (29.50)	15.48 (22.24)	<0.001
Hispanic, %	24.20 (24.61)	27.76 (26.70)	20.64 (21.75)	<0.001
Economy				
Unemployment rate, %	9.03 (5.71)	10.11 (6.24)	7.96 (4.90)	<0.001
GINI index	0.43 (0.06)	0.44 (0.06)	0.42 (0.06)	<0.001
Population in poverty, %	27.21 (17.14)	32.45 (17.36)	21.98 (15.21)	<0.001
Per capita income, 1000$	29.97 (17.59)	27.41 (17.76)	32.53 (17.03)	<0.001
Education				
Master's degree, %	12.14 (10.56)	11.21 (10.73)	13.08 (10.29)	<0.001
Bachelor's degree, %	19.57 (11.20)	18.02 (11.34)	21.11 (10.85)	<0.001
College degree, %	27.99 (8.08)	26.54 (8.05)	29.43 (7.85)	<0.001
Only high school diploma, %	24.42 (9.91)	25.30 (10.01)	23.54 (9.73)	<0.001
Less than high school, %	15.89 (12.67)	18.92 (13.35)	12.85 (11.16)	<0.001
Urbanization				
Large central metro, %	61 (49)	72 (45)	50 (50)	<0.001
Large fringe metro, %	12 (33)	10 (30)	14 (35)	<0.001
Medium metro, %	22 (42)	15 (36)	29 (45)	<0.001
Small metro, %	5 (22)	3 (17)	7 (25)	<0.001
Health Behavior				
Binge drinking, %	17.36 (3.61)	17.22 (3.91)	17.50 (3.29)	<0.001
Environment				
NO_2, μ/m^3	12.20 (3.93)	13.92 (3.46)	10.48 (3.61)	<0.001
PM2.5, μ/m^3	8.59 (1.68)	8.85 (1.68)	8.33 (1.64)	<0.001
Mean temperature, °C	17.61 (5.43)	17.90 (5.64)	17.32 (5.26)	<0.001

Note. The values were presented as mean (SD) for continuous variables or percentage (SD) for categorical variables. Abbreviations: SD, standard deviation; Obtained using the chi-squared test for categorical variables and *t*-test for continuous variables. See the main text for additional details on variable definitions and data sources.

areas and radiate toward suburbia. The results of the Spearman correlation analysis indicated a weak positive correlation between population-weighted O-ALAN and the prevalence of both frequent mental health ($\beta = 0.21$) and short sleep duration ($\beta = 0.28$) (Fig. 4). Additionally, a strong correlation was observed between frequent mental health issues and short sleep duration ($\beta = 0.71$).

3.2. Impacts of O-ALAN on mental health and sleep

We find that the percentage of the population living below 1.37 times the poverty threshold is a strong predictor of population-weighted O-ALAN levels across census tracts. On average, a 1 % increase in the population below this threshold raises the logarithm of population-weighted O-ALAN by approximately 0.0178. This is consistent with the evidence that disadvantaged urban neighborhoods exhibit elevated ALAN levels due to denser infrastructure and limited light pollution regulations (Paksarian et al., 2020). The first-stage regression demonstrated robust instrument relevance, with an F-statistic of 586.1 ($p < 0.001$), confirming no weak instrument bias. Multicollinearity checks revealed no substantive issues (mean VIF = 2; all VIFs <5).

The estimates from the second-stage regression are listed in Table 2. Using the percentage of the population in poverty (1.37 times of below the poverty threshold) as an instrumental variable for population-weighted O-ALAN, we found that a ten-fold increase in O-ALAN leads to an 8.05 % (±0.04 %) rise in the prevalence of frequent mental distress and a 4.99 % (±0.07 %) rise in the prevalence of short sleep duration. Both coefficients are highly statistically significant ($p < 0.001$). Our analysis with an adjustment of NO_2 resulted in higher estimates of the O-ALAN's effects. A tenfold increase in O-ALAN leads to a 12.27 % (±0.14 %) rise in the prevalence of frequent mental distress and a 7.83 % (±0.13 %) rise in the prevalence of short sleep duration, with both coefficients remaining statistically significant ($p < 0.001$) (Table S1).

To evaluate potential spatial confounding, we incorporated state-level fixed effects in sensitivity analyses. The association remained robust, with coefficients higher than primary estimates. State-specific effects varied, with stronger negative associations observed in states with stringent light pollution regulations (e.g., Colorado). Smaller states exhibited wider confidence intervals due to limited sample sizes (Supplementary Table S2 and S3).

3.3. Disparities of impacts by education and urban-rural context

To advance our understanding of the mechanisms linking O-ALAN to the prevalence of frequent mental distress and short sleep duration, we explore heterogeneous relationships. Greater sensitivity in a specific subset (e.g., lower-education areas) indicates that distinct mechanisms drive the aggregate effects observed in the full sample. We divide the data into subsets based on education level, urban-rural categories, and the spatial characteristics of each census tract, and re-estimate our primary model for each subset. In this scenario, census tracts with a higher percentage of population holding master's degrees, bachelor's, or associate's degrees are associated with a lower prevalence of both frequent mental distress and short sleep duration. Conversely, census tracts with a higher percentage of the population possessing only a high school diploma or less exhibit a higher prevalence of these two health risk conditions (Table 3).

We find strong evidence of differential O-ALAN effects on the prevalence of health risk conditions across census tracts of different education levels (Fig. 5). The prevalence of frequent mental distress in census tracts with a higher percentage of populations possessing only a high school diploma is less sensitive to O-ALAN compared to other subgroups. The prevalence in the first quartile increased by 7.58 % (±0.07 %) for each ten-fold increase in O-ALAN, whereas the coefficient in the fourth quartile is 6.91 % (±0.08 %). Similarly, census tracts with the highest percentage of populations holding bachelor's and master's degrees were far more sensitive to O-ALAN than others. Regarding short sleep duration, the effects across subgroups with different education levels showed different trends from frequent mental distress. The largest impact of O-ALAN was observed in census tracts with the highest percentage of populations with less than a high school diploma (2.15 % ± 0.17 % for Q1 and 3.48 % ± 0.13 % for Q4). We also found that census tracts with the lowest percentage of populations holding master's and bachelor's degrees were far more sensitive to O-ALAN than those with more highly educated populations.

Notably, the effects of O-ALAN on frequent mental distress and short sleep duration show different trends when they are categorized into quartiles, respectively. Specifically, in frequent mental distress, the association across college degree quartiles mirrored the trend across lower education groups quartiles (e.g., those with only a high school diploma),

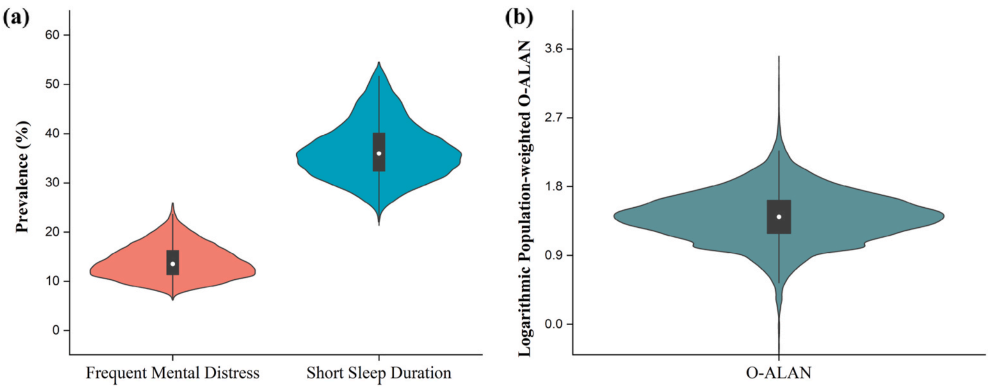

Fig. 2. Statistical distribution of **(a)** the prevalence of frequent mental distress and short sleep duration, and **(b)** the population-weighted O-ALAN (nW/cm^{2}sr).

presenting a smaller impact in census tracts with more population holding college degrees (9.07 % ± 0.07 % for Q1 and 7.41 % ± 0.08 % for Q4). While in short sleep duration, the trend aligned with the pattern found in higher education strata (master's and bachelor's degrees), showing greater impact in areas with more college-educated populations (6.59 % ± 0.15 % for Q1 and 3.49 % ± 0.14 % for Q4).

The variation in the association between population-weighted O-ALAN and the prevalence of health risk conditions across urbanization levels also suggests the added value of research in different geographic settings (Fig. 6). Our sample covered four groups in the 2013 Urban-Rural Classification Scheme: (i) large central metro, (ii) large fringe metro, (iii) medium metro, and (iv) small metro. In this case, it was found that from rural to most urbanized areas, the prevalence of frequent mental distress increases, and become more sensitive to O-ALAN at the same time A tenfold increase in O-ALAN is associated with a 5.24 % (±0.13 %), 5.60 % (±0.07 %), 6.52 % (±0.09 %), and 6.98 % (±0.04 %) increase in the prevalence of frequent mental distress in small metro, medium metro, large fringe metro, and large central metro, respectively. Similarly, the impact of ALAN on short sleep duration follows the same trend across urbanization levels. However, the highest impact of O-ALAN on the prevalence of short sleep duration was found in the more but not the mostly urbanized areas.

4. Discussion

4.1. Main findings

This study provides robust evidence that higher population-weighted O-ALAN is associated with an increased prevalence of frequent mental distress and short sleep duration across census tracts in 500 major US cities. Using a 2SLS model to account for economic endogeneity, we found that a tenfold increase in O-ALAN was associated with an 8.05 % rise in mental distress prevalence and a 4.99 % increase in short sleep duration prevalence. We observed significant heterogeneity in these associations. Educational attainment modified ALAN's effects, with higher education levels intensifying its negative impact on mental health but attenuating its effect on sleep. Urbanization amplified ALAN's adverse effects, with stronger associations observed in highly urbanized areas, though the impact on sleep was most pronounced in moderately urbanized regions. These findings highlight O-ALAN as a potential environmental risk factor that varies across different socioeconomic and spatial contexts.

4.2. Interpretation and implications

We humbly argue that this study shall be among the pioneer studies to reveal the relationships between O-ALAN and sleep and mental health. Previous studies across different population samples have reported significant associations between O-ALAN and sleep duration and quality (Paksarian et al., 2020; Vollmer et al., 2012). While previous research has not consistently observed a relationship between outdoor and indoor ALAN, the cumulative evidence supports the idea that O-ALAN contributes to sleep deprivation. Our findings align with these studies, demonstrating that greater O-ALAN exposure is associated with a higher prevalence of self-reported short sleep duration across the US population.

Notably, a prior ecological study in the US employed average O-ALAN as a measure and identified a weak association between light exposure and reduced sleep, revealing minimal population-level effects (Patel, 2019). This discrepancy may stem from the limitations of simply using averages, which can misestimate actual population exposure to light. In contrast, we utilized population-weighted O-ALAN to more accurately capture O-ALAN exposure of populations, yielding significant effects. This measurement is designed to capture the O-ALAN level around one's residence. Simply averaging the O-ALAN values of all pixels in a unit of an administrative area may be problematic and misleading, as the population density and O-ALAN are usually heterogeneous over time and space in each census tract. To address this issue, we proposed the population-weighted O-ALAN that accounts for the wide variation in O-ALAN across the areas by using population as a weighting factor. To illustrate, consider a census tract composed of two sub-areas: one has a high O-ALAN level but a small area and a large population, and the other has a low O-ALAN level but a large area and a small population. A simple average would yield homogeneous O-ALAN values for the entire census tract. In comparison, the population-weighted O-ALAN can effectively highlight higher O-ALAN levels, which theoretically correspond to more human activities and residence. Thus, the population-weighted ALAN better captures the O-ALAN exposure relevant to the health behaviors of most residents. However, air pollutants and temperature are influenced by atmospheric mixing and regional weather patterns, leading to relatively uniform distributions within census tracts, which were thus measured by the mean value. Additionally, a study from the Netherlands found that, when using NO_2 as the air pollution metric for adjustment, the correlation was no longer significant (Helbich et al., 2020). In light of this, we conducted a repeated analysis adjusting for NO_2 instead of PM2.5, and found that associations between O-ALAN and the prevalence of frequent mental distress remained significant. Consistent with previous research, our findings reinforce the notion that O-ALAN is an environmental factor significantly impacting sleep and mental well-being.

We also observed several important trends regarding the relationship between O-ALAN, health outcomes, and education levels. The heightened sensitivity of educated populations to mental health impacts could reflect occupational stressors or reduced physiological resilience despite greater access to healthcare resources (Abulfaraj et al., 2024). Conversely, the stronger association between O-ALAN and sleep deprivation in less-educated areas may stem from limited access to light-mitigating infrastructure (e.g., blackout curtains) or

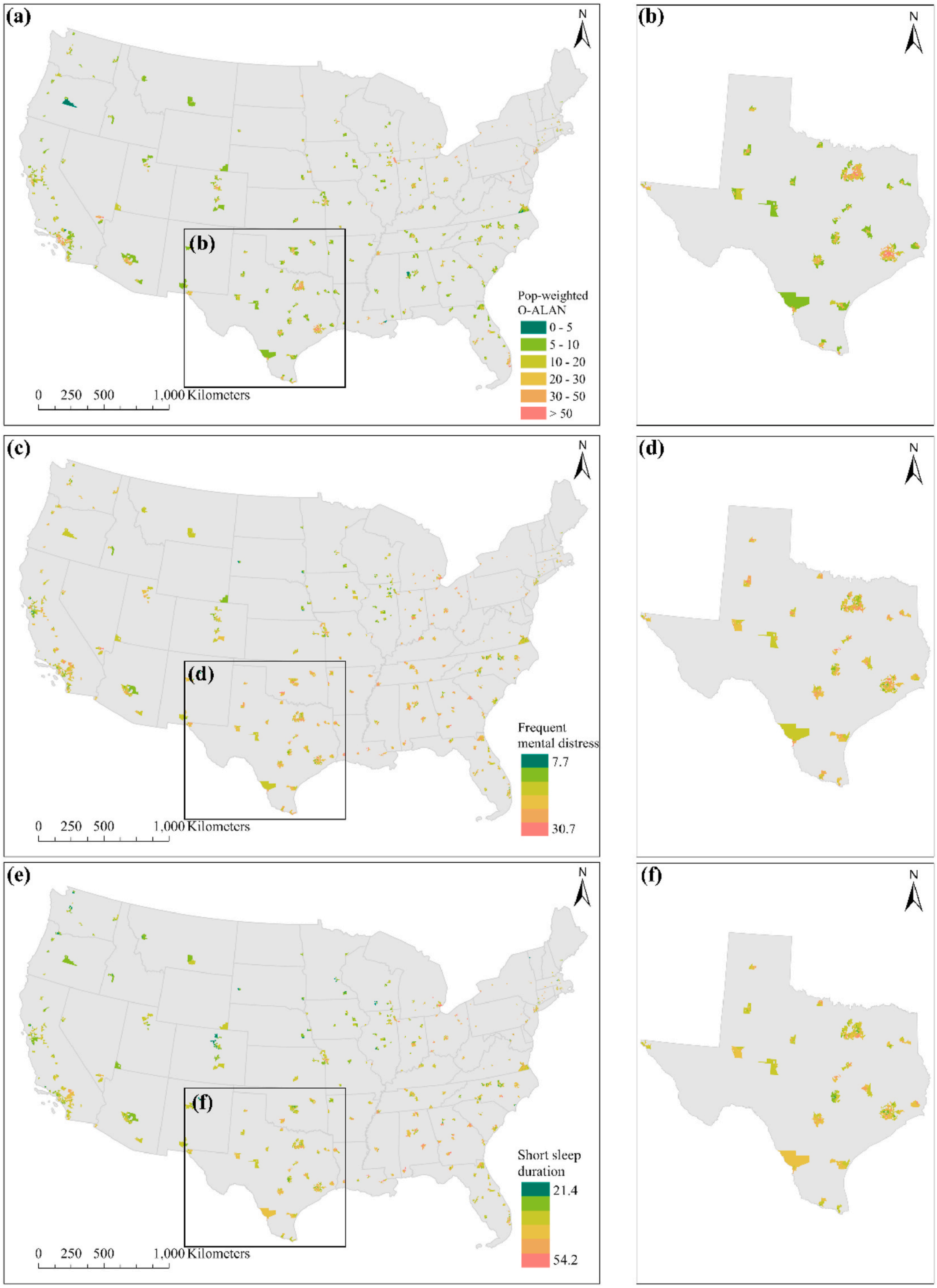

Fig. 3. Spatial distribution of population-weighted outdoor artificial light at night (O-ALAN), prevalence of frequent mental distress, and prevalence of short sleep duration across census tracts within the 500 Cities Project in the United States. Panels (a), (c), and (e) depict the national distribution of these variables; panels (b), (d), and (f) provide a detailed view of distribution zoomed to Texas, an example state for viewing spatial variations more clearly.

socioeconomic vulnerabilities (Shao et al., 2022). Urbanization trends further highlight the interplay between environmental stressors and population density, where rapid development in moderately urbanized areas may outpace regulatory measures to control light pollution. These results advocate for targeted interventions. Urban planners and policymakers should prioritize light pollution reduction in densely populated regions through zoning regulations (e.g., shielded lighting) and public health campaigns. Additionally, socioeconomic disparities in O-ALAN exposure emphasize the need for equitable resource allocation to mitigate environmental inequities.

4.3. Limitations

There are several limitations to our study that bear mentioning. First, a key limitation is the potential for ecological fallacy. Population-weighted O-ALAN, though an improvement over simple averages,

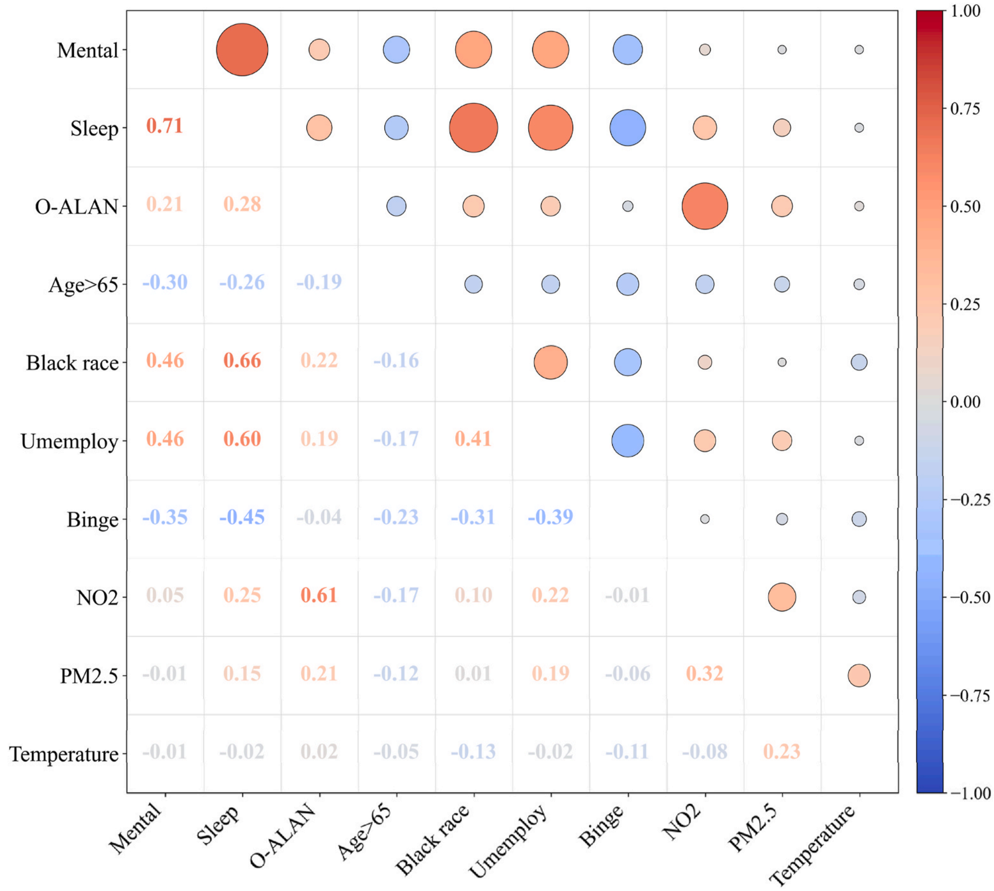

Fig. 4. Correlations between prevalence of frequent mental distress, short sleep duration, population weighted ALAN, and covariates. **Note**: See main text for additional details on variable definitions and data sources. Significant signs for correlation coefficients are marked in the circles.

Table 2
Estimates of the association between Population-weighted O-ALAN and prevalence of frequent mental distress and short sleep duration.

Variable	Frequent Mental Distress		Short Sleep Duration	
	Estimate (95 % CI)	*p*	Estimate (95 % CI)	*p*
O-ALAN	8.05 (8.01, 8.09)	<0.001	4.99 (4.92, 5.06)	<0.001
Age>65	−0.11 (−0.12, −0.10)	<0.001	−0.17 (−0.17, −0.17)	<0.001
Black race	0.04 (0.04, 0.04)	<0.001	0.08 (0.08, 0.08)	<0.001
Unemployment	0.13 (0.13, 0.13)	<0.001	0.17 (0.16, 0.17)	<0.001
Binge	−0.47 (−0.47, −0.47)	<0.001	−0.50 (−0.50, −0.49)	<0.001
$PM_{2.5}$	−0.66 (−0.67, −0.65)	<0.001	−0.15 (−0.16, −0.15)	<0.001
Temperature	−0.05 (−0.05, −0.04)	<0.001	−0.02 (−0.02, −0.02)	<0.001
Year_2014	0.50 (0.47, 0.53)	<0.001	0.32 (0.27, 0.38)	<0.001
Year_2015	1.28 (1.25, 1.31)	<0.001	0.72 (0.67, 0.78)	<0.001
Year_2016	2.17 (2.14, 2.20)	<0.001	1.19 (1.13, 1.25)	<0.001
Year_2017	2.91 (2.88, 2.94)	<0.001	2.23 (2.18, 2.29)	<0.001
Year_2018	4.22 (4.19, 4.25)	<0.001	2.57 (2.52, 2.63)	<0.001
Year_2019	3.63 (3.60, 3.66)	<0.001	−0.63 (−0.69, −0.57)	<0.001

Note: The year 2013 served as the reference (baseline) year in all regression models. Coefficients for subsequent years (2014–2019) represent changes in prevalence relative to 2013.

Table 3
Relative differences in the impact of educational attainment on frequent mental distress and short sleep duration across quartiles.

Frequent Mental Distress	Q1	Q2	Q3	Q4
Master's degree	ref	−1.52 (−1.56, −1.48)	−3.14 (−3.18, −3.09)	−6.24 (−6.29, −6.19)
Bachelor's degree	ref	−1.92 (−1.96, −1.88)	−3.56 (−3.60, −3.51)	−5.84 (−5.89, −5.79)
College degree	ref	5.30 (5.24,5.36)	7.99 (7.92, 8.07)	9.58 (9.49,9.67)
High school diploma	ref	2.60 (2.56, 2.64)	4.29 (4.25,4.34)	5.39 (5.34,5.44)
Lower than High School	ref	0.85 (0.81, 0.90)	0.67 (0.62,0.73)	−0.29 (−0.36, −0.22)
Short Sleep Duration	Q1	Q2	Q3	Q4
Master's degree	ref	−1.19 (−1.24, −1.13)	−2.72 (−2.79, −2.66)	−5.45 (−5.53, −5.38)
Bachelor's degree	ref	−1.41 (−1.47, −1.35)	−3.08 (−3.15, −3.02)	−5.57 (−5.65, −5.50)
College degree	ref	2.78 (2.69, 2.87)	3.97 (3.86, 4.09)	4.77 (4.64, 4.91)
High school diploma	ref	2.74 (2.68, 2.80)	4.26 (4.20, 4.33)	5.43 (5.36, 5.50)
Lower than High School	ref	1.80 (1.74, 1.87)	2.79 (2.72, 2.87)	3.27 (3.18, 3.37)

population-level analyses cannot disentangle individual behaviors or biological responses that mediate O-ALAN's effects. Second, self-reported health outcomes may introduce recall or social desirability bias, though the use of age-adjusted prevalence mitigates some measurement errors. This subjectivity could introduce bias in the estimated results. Third, while the 2SLS instrumental variable approach helps address endogeneity concerns, residual confounding from

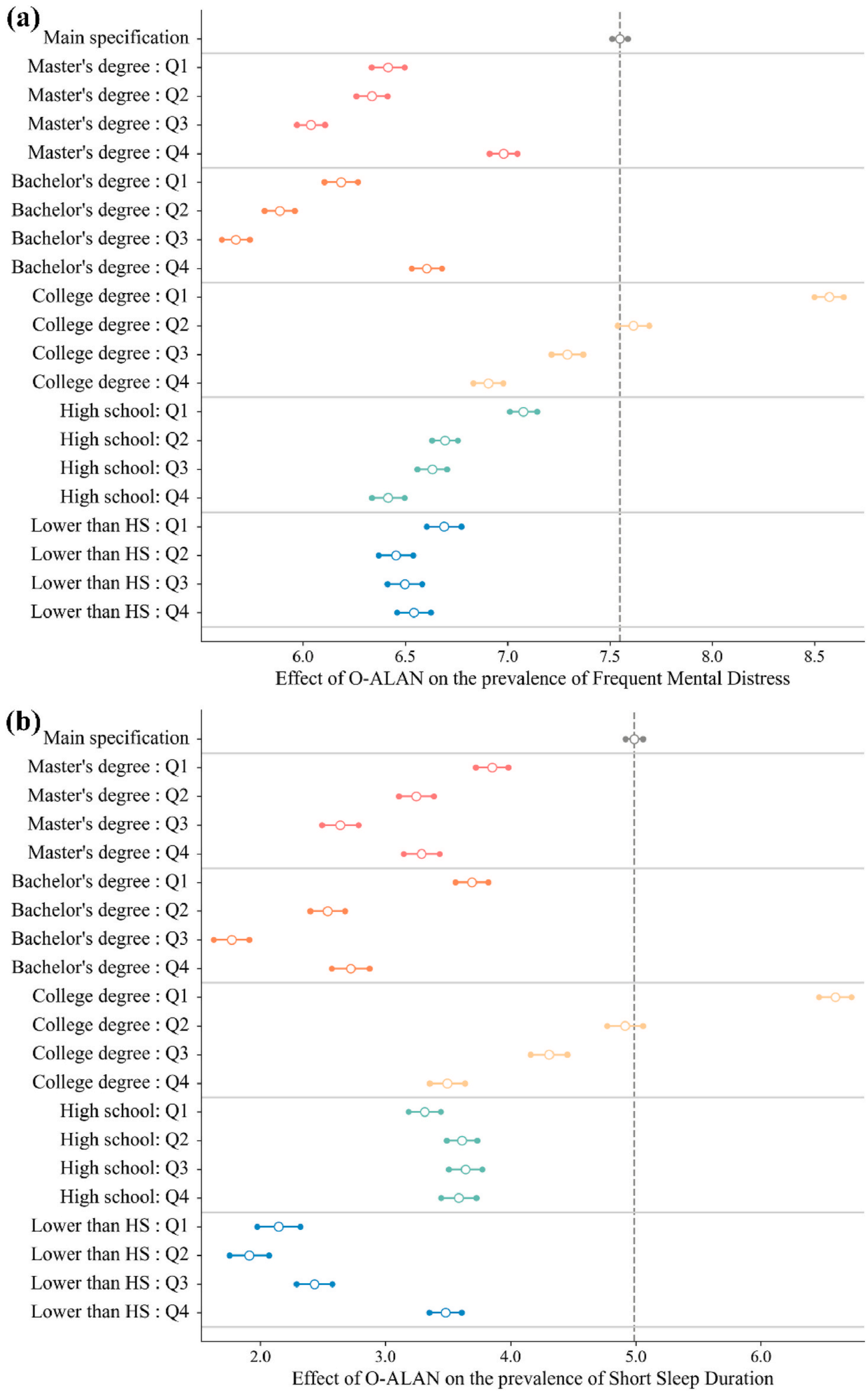

Fig. 5. Heterogeneous effects of O-ALAN on the prevalence of frequent mental distress and short sleep duration in areas with different education levels. The point estimate and associated confidence intervals for the main specification are shown in grey. All other estimates use subsamples of the data, splitting by the percentage of population obtaining a master's degree (red), bachelor's degree (orange), college degree (yellow), only high school diploma (green), and lower than high school diploma (blue).

unmeasured variables cannot be entirely ruled out. Socioeconomic factors, urban infrastructure, and environmental stressors may interact with ALAN exposure in complex ways that our model may not fully capture. Additionally, due to data constraints, our analysis could not include important health factors such as BMI, chronic diseases, or physical activity, which may confound the associations between ALAN and sleep. Fourth, satellite-derived O-ALAN data do not differentiate between direct outdoor exposure and indoor light leakage, limiting precise exposure assessment (Liu and Kwan, 2024), and the ecological paradigm limits causal inference and mechanistic exploration. Individual-level O-ALAN exposure measures and health studies may provide stronger evidence, but require finer O-ALAN exposure

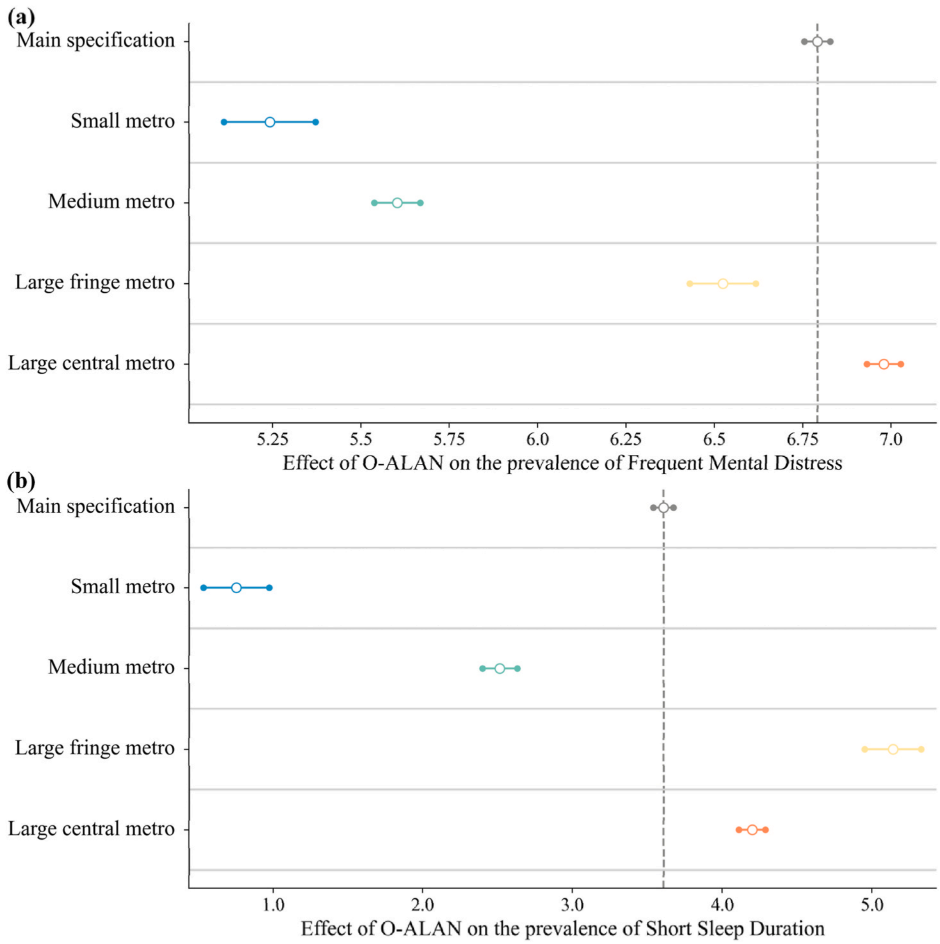

Fig. 6. Heterogeneous effects of O-ALAN on the prevalence of frequent mental distress and short sleep duration in areas with different urbanization levels. The point estimate and associated confidence intervals for the main specification are shown in grey. All other estimates use subsamples of the data, splitting by the urban-rural category.

measures. Longitudinal designs tracking urbanization-driven changes in light pollution and health outcomes could clarify temporality and refine policy interventions. Furthermore, green space and meteorological variables such as humidity and wind speed were not incorporated due to data limitations, though they may also contribute to variations in sleep and mental health. Finally, although both frequent mental distress and short sleep duration were examined independently, we acknowledge that these two outcomes may have a bidirectional or mediating relationship. Future research could apply structural equation modeling or longitudinal mediation analysis to explore potential causal chains or feedback mechanisms linking sleep and mental health.

5. Conclusion

This study identifies strong positive correlations between higher population-weighted O-ALAN and increased prevalence of both frequent mental distress and short sleep duration. The effects of O-ALAN varied across different education levels. High educational attainment exacerbates the adverse impact of O-ALAN on frequent mental distress. In contrast, for short sleep duration, low educational attainment exacerbates the adverse impact of O-ALAN. Moreover, our analysis across urban-rural categories shows that O-ALAN's influence on these health outcomes intensifies as areas become more urbanized, though the strongest effect on short sleep duration was observed not in the most urban, but in moderately urbanized areas. Given that O-ALAN represents a preventable and modifiable exposure, continued investigation into its potential links with various health outcomes remains essential.

CRediT authorship contribution statement

Ruoyu Dong: Writing – original draft, Methodology, Investigation, Formal analysis. **Yanqing Xu:** Writing – review & editing, Validation, Supervision, Funding acquisition. **Rui Zhu:** Writing – review & editing, Supervision, Resources, Investigation, Conceptualization.

Acknowledgement

This study was supported by the National Natural Science Foundation of China (42471444), the Joint Foundation for Translational Medicine and Interdisciplinary Research from Zhongnan Hospital of Wuhan University (ZNJC202301), the Fundamental Research Funds for the Central Universities (2042024kf0017), and the Interdisciplinary Innovative Talents Foundation from Renmin Hospital of Wuhan University (JCRCYG-2022-013).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2025.103504.

Data availability

Data will be made available on request.

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