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Light pollution inequities in the continental United States: A distributive environmental justice analysis

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ABSTRACT

Excessive exposure to ambient light at night is a well-documented hazard to human health, yet analysts have not examined it from an environmental justice (EJ) perspective. We conducted the first EJ study of exposure to light pollution by testing for socially disparate patterns across the continental United States (US). We first calculated population-weighted mean exposures to examine whether ambient light pollution in the US differed between racial/ethnic groups. We then used multivariable generalized estimating equations (GEEs) that adjust for geographic clustering to examine whether light pollution was distributed inequitably based on racial/ethnic composition and socioeconomic status across US neighborhoods (census tracts). Finally, we conducted a stratified analysis of metropolitan core, suburban, and small city–rural tracts to determine whether patterns of inequity varied based on urban-rural context. We found evidence of disparities in exposures to light pollution based on racial/ethnic minority and low-to-mid socioeconomic statuses. Americans of Asian, Hispanic or Black race/ethnicity had population-weighted mean exposures to light pollution in their neighborhoods that were approximately two times that of White Americans. GEEs indicated that neighborhoods composed of higher proportions of Blacks, Hispanics, Asians, or renter-occupants experienced greater exposures to ambient light at night. Stratified analyses indicated that those patterns of inequity did not substantially vary based on urban-rural context. Findings have implications for understanding environmental influences on health disparities, raise concerns about the potential for a multiple environmental jeopardy situation, and highlight the need for policy actions to address light pollution.

1. Introduction

Concerns about pollution overburdening disadvantaged groups in the United States (US) catalyzed the environmental justice (EJ) movement and motivated activists, researchers, and policymakers for nearly forty years. EJ emphasizes social equitability, both in terms of environmental quality and access to environmental decision-making processes (Bryant, 1995). EJ analyses initially focused on the sociospatial distribution of toxic pollution, providing evidence for disparate exposures based on minority racial/ethnic and low socioeconomic statuses (Brulle and Pellow, 2006; Nadybal et al., 2020). A United Church of Christ (UCC, 1987) sponsored study was the first to identify a positive relationship between racial/ethnic minority composition and the number of toxic waste facilities across US postal code areas. The initial EJ analyses that followed also focused on toxic waste, by examining proximity to landfills and Superfund sites (i.e., contaminated areas needing long-term remediation) (Brown, 1995; Bullard, 2000; Cutter, 1995). The field then expanded to examine unequal exposure to air pollution (Ard, 2015; Collins et al., 2015; Grineski et al., 2007; Maantay, 2007). EJ studies of toxic waste and air pollution provided overwhelming evidence that racial/ethnic minority and economically-deprived populations experienced disparate exposures.

Over the past decade, studies have expanded the scope of the EJ field by examining social inequities in access to environmental amenities and in exposures to a broader range of technological hazards. In terms of environmental amenities, EJ analysts have documented inequities in access to parks, beaches, and green space based on indicators of social disadvantage (Dahmann et al., 2010; Montgomery et al., 2015; Sister et al., 2010). With the increasing salience of climate change-related hazards such as urban heat and flooding, an emergent line of EJ research has found that racial/ethnic minority and lower socioeconomic statuses are associated with exposures to higher land surface

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temperatures (Harlan et al., 2007; Voelkel et al., 2018) and greater flooding (Chakraborty et al., 2019; Collins et al., 2019a). Most recently, EJ analyses in the US focused on noise pollution have found that racial/ethnic minorities live or attend school in louder areas, potentially contributing to poorer health and educational outcomes (Casey et al., 2017; Collins et al., 2019b, 2020).

While EJ research has expanded in important ways since the late 1980s, studies have not yet evaluated potential social inequities in exposure to ambient (i.e. outdoor) light at night. This is despite the fact that the excessive use of artificial light at night is an emergent, rapidly intensifying environmental hazard known to disturb sleep patterns, trigger mental illnesses, and increase risks of various cancers in humans (Anisimov, 2006; Gaston et al., 2013; Haim and Portnov, 2013; Hölker et al., 2010). In order to improve knowledge and practice, it is important to assess whether the distribution of light pollution reflects the socially inequitable patterns observed for other environmental hazards.

1.1. Light pollution: an emergent environmental health hazard

The use of artificial lighting at night is a relatively recent development. Electric lighting was first created in 1879 and has since been used to increase time for economic and recreational activities, promote a greater sense of safety, and ensure efficient transportation in communities (Chepesiuk, 2009; Doleac and Sanders, 2015; Falchi et al., 2019; Haim and Portnov, 2013; Reiter et al., 2007; Sullivan and Flannigan, 2002). The benefits of artificial lighting clarify why it is widely used throughout the world and help to explain its increasing presence in residential, recreational, and commercial environments (Kyba et al., 2017). Increases in the usage of artificial light at night are evident from analyses of remotely-sensed images, which indicate that upwards of 80% of the world's population live under night skies that have been artificially brightened (Cinzano et al., 2001; Falchi et al., 2016a; Rabaza et al., 2010). While spatial variations related to physical geography, economic productivity, and regional governance of lighting may influence the distribution of ambient light at night, artificial lighting has become a prevalent feature across much of the modern world.

Ambient light pollution, or the excessive usage of outdoor artificial lighting at night, is one of the fastest growing and most pervasive hazards in the contemporary environment (Chepesiuk, 2009). Much of the concern about ambient light pollution stems from its impact on human health, as increased personal exposure to artificial lighting is associated with severe ailments. Chronodisruption, or the disruption of organisms' circadian rhythms, is among the most important impairments. Humans are diurnal creatures that have physiologically adapted to the natural progression of day and night. This adaptation has led to the development of a network of neurons in the brain that is responsible for regulating physiological responses to light exposure (Bedrosian and Neslon, 2017; Reiter et al., 2009; Smolensky et al., 2015). These responses—which encompass neuronal activities (Escobar et al., 2011; Reiter et al., 2009), brain wave patterns (Chepesiuk, 2009), cell regulation (Chepesiuk, 2009), and the production and secretion of hormones (Haim and Zubidat, 2015; Kantermann and Roenneberg, 2009; Reiter at al., 2011)—naturally occur during periods of daylight but can be disrupted by exposure to artificial light at night.

Decreased melatonin levels cause the most severe ailments related to chronodisruption. Melatonin, the hormone responsible for regulating humans' sleep-wake patterns, requires extended periods of darkness for production and circulation throughout the body (Kanterman and Roenneberg, 2009; Reiter et al., 2007, 2011). As such, it is difficult for humans to maintain regular sleep cycles in light-polluted environments (Pauley, 2004; Raap et al., 2015; Smolensky et al., 2015). Sleep disorders associated with reduced melatonin levels are linked to higher rates of anxiety, depression (Chepesiuk, 2009), and obesity (Wyse et al., 2011), which increase human risks for cardiovascular diseases (Eckel et al., 1998; Zhou et al., 2000), diabetes (Mokdad et al., 2003), gastrointestinal disorders (Delgado-Aros et al., 2004; Donohoe et al., 2010), and neurological ailments such as strokes and multiple sclerosis (Hedström et al., 2012; Winter at al., 2008).

Earlier research on artificial light and human health focused on individuals' nighttime exposures within indoor occupational and residential settings, and found associations between greater exposures and increased cancer risks. Exposures to artificial light at night via shiftwork or home-based personal behavior were found to increase women's risks of breast, colorectal and lung cancers (Davis et al., 2001; Hansen et al., 2001; Kloog et al., 2011; Schernhammer and Hankinson, 2003; Schernhammer et al., 2001, 2006, 2013); and men's risks of prostate, lung, colon, bladder and pancreatic cancers (Conlon et al., 2007; Papantoniou et al., 2014; Parent et al., 2012). While those studies adjusted for covariates and established causal linkages between nighttime light exposure and cancer, they did not consider the effects of ambient (outdoor) sources of exposure to artificial light at night.

A more recent wave of individual-level studies has documented human health effects of residential exposure to ambient light at night. Most such studies have measured ambient light at night based on residential locations using Defense Meteorological Satellite Program (DMSP) imagery. Several studies found associations between greater ambient light at night and increased risks for breast cancer in women, adjusting for factors such as race, income, and familial history of breast cancer (Bauer et al., 2013; Hurley et al., 2014; James et al., 2017). Garcia-Saenz et al. (2018) found that men and women residing in brighter areas of Barcelona and Madrid, Spain, were at a higher risk for prostate and breast cancer when compared to residents living in darker areas. In an individual-level analysis of sleep duration in middle-to-older aged adults in the US, Xiao et al. (2020) found that higher levels of ambient light at night predicted shorter periods of sleep, controlling for other relevant factors.

Ecological studies of ambient light at night—i.e., analyses using aggregated population data to examine the group-level effects of exposures to outdoor light pollution—have produced results similar to those from individual-level studies of indoor and outdoor exposures. Several global analyses of light pollution using DMSP nighttime imagery found strong associations between ambient light at night and breast cancer in women (Kloog et al., 2008; Rybnikova et al., 2015) and prostate cancer in men (Kloog et al., 2009; Rybnikova et al., 2017), adjusting for variables such as income, urbanicity, and electricity consumption. In studies of South Korea, Kim et al. (2015, 2017) found that higher levels of ambient light at night predicted increased risks for breast cancer in women and prostate cancer in men. In a neighborhood (census tract) level analysis of ambient light pollution (using DMSP imagery) in Connecticut, USA, Portnov et al. (2016) found that women residing in brighter neighborhoods had an increased risk for breast cancer, adjusting for factors such as urbanicity, poverty level, and fertility rate.

Given the well-documented human health effects of light pollution, there is a clear gap in knowledge pertaining to potential social inequities in exposure. There are three reasons why we hypothesize that racial/ethnic minority status and low socioeconomic status relate to disproportionate exposure to light pollution. First, the EJ literature has documented how locally unwanted land use activities—some of which emit high levels of artificial nighttime light—cluster in socially disadvantaged US communities where minority and low-income residents concentrate. Second, with knowledge of the human and ecological impacts of light pollution expanding over the past two decades, artificial nighttime light from a societal perspective has become increasingly undesirable. It is plausible that the treatment of nighttime darkness as an environmental amenity and the implementation of "dark sky" initiatives—almost exclusively in privileged US communities where White and affluent residents concentrate—has influenced social inequities in exposure to light pollution. Third, US society has long criminalized particular racial/ethnic minority groups, and it is possible that this has served to justify the deployment of greater artificial lighting in socially disadvantaged neighborhoods as a means to support nighttime policing and surveillance by law enforcement authorities.

This paper aims to extend knowledge by quantifying social inequities in exposure through the first EJ assessment of ambient light pollution. We conducted a cross-sectional analysis of disparities in exposure based on remote sensing-derived measures of light pollution across the continental US and a stratified analysis of metropolitan core, suburban, and rural neighborhoods. We addressed three questions: (1) How does the population-weighted mean exposure to ambient light pollution differ between racial/ethnic groups in the US? (2) Is ambient light pollution in the US distributed inequitably at the neighborhood (census tract) level with respect to racial/ethnic composition and socioeconomic status (SES), after adjusting for geographic clustering and relevant variables? (3) How do patterns of inequity in the distribution of ambient light pollution in the US vary across the urban-rural continuum?

2. Methods and materials

2.1. Study population

We downloaded publicly available data from the US Census Bureau website on the geographic boundaries and sociodemographic composition of census tracts in the lower 48 states and Washington, DC. We used 2012–2016 ACS five-year estimates because they include all variables of analytical interest and center on 2014—the year *The new world atlas of artificial night sky brightness* (hereafter denoted as the "*atlas*") most recently calculated light pollution estimates (Falchi et al., 2016a). As per many other US-based EJ studies, we selected the census tract as our analysis unit since it represents the finest scale for which reliable ACS five-year estimates are available. We excluded census tracts with less than 500 residents and incomplete data to ensure stable proportional estimates for all variables, and included data for 70,358 census tracts in our analysis.

2.2. Dependent variable

We measured artificial light at night using spatial data from the *atlas* (Falchi et al., 2016a, 2016b). The *atlas* defines light pollution as any level of radiance surpassing 174 μcd/m^2 (i.e., 0.174 mcd/m^2), as this is the natural level of light present in the night sky during zenith. To measure ambient light at night, the *atlas* used low-light imaging data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night band (DNB) sensor aboard the Suomi National Polar-orbiting Partnership (NPP) satellite. The DNB sensor achieves global coverage of light pollution with a swath width of 3000 km and a spatial resolution of 742 m. At the time of writing, data from the VIIRS DNB sensor had better linear resolution and range than any other satellite instrument used to measure nocturnal radiance (Falchi et al., 2016a, 2016b). Additionally, VIIRs DNB incorporates the use of in-flight calibration, a higher spatial resolution and bit quantization, and has a more dynamic range when compared to other satellite instruments used in light pollution-health studies (Elvidge et al., 2013).

Clouds, lightning, and fires can obstruct remote sensing observations of artificial light at night. To produce spatially comprehensive nocturnal light measures, the *atlas* incorporated the use of composite products created by the Earth Observation Group (EOG) at the US National Oceanic and Atmospheric Administration's National Centers for Environmental Information (Baug et al., 2013). These composite products were generated as monthly 15-arcsecond grids, with each grid cell representing the average radiance value calculated by the DNB sensor. The composite products only included DNB data from cloudless nights that were unaffected by moonlight or other forms of ephemeral lighting, as this ensured the most accurate measurements of artificial light pollution. Composite products for May, June, September, October, November, and December of 2014 were then combined into one 6-month composite, also generated as a 15-arcsecond grid, for sky brightness modeled by the *atlas*. Each grid cell within the 6-month composite represented the average radiance value. In order to increase the accuracy of light pollution estimates, data from the DNB composite product were propagated through the atmosphere using a radiative transfer code (Falchi et al., 2016a, 2016b). The radiative transfer code assisted in calibrating raw light pollution estimates to account for how artificial light at night travels through Earth's atmosphere. Falchi et al. (2016a, 2016b) and Cinzano and Falchi (2012) provide detailed information on the radiative transfer code and upward emission function as well as the specific calibrations used. The *atlas* data used for our analysis were available as a 30-arcsecond grid (Falchi et al., 2016a, 2016b).

To create our dependent variable for analyzing social inequities in light pollution exposure across US census tracts, we overlaid the artificial radiance data from the *atlas* onto census tract boundaries using ArcGIS Pro (Esri, 2019). We then used zonal statistics to determine the mean artificial radiance value of the *atlas* light pollution pixels within each census tract. Zonal statistics allow for the calculation of statistics within user-defined zones, such as census tracts, based on values from a supplementary dataset, such as the *atlas* light pollution grid. We used the polygon containment approach, which required each light pollution pixel to be completely contained by a census tract boundary for inclusion in the calculation of mean artificial radiance. To minimize the impact of boundary effects based on polygon containment and ensure that every census tract contained at least one *atlas* light pollution pixel for calculating mean artificial radiance using zonal statistics, we reduced the cell size of the light pollution pixels from 30-arcsecond (i.e., approx. 926-by-712 m) to 88-by-88 m. Units for our dependent variable are reported in mcd/m^2 (Falchi et al., 2016b).

To illustrate the zonal statistics procedure, Fig. 1 shows raw pixel data and the output from the zonal statistics process for Los Angeles County, California. It reveals a high degree of correspondence between the raw radiance grid values from the *atlas* (Fig. 1, left) and the resulting measure of mean radiance assigned to census tracts (Fig. 1, right). To enable visual comparison, the map of census tracts (Fig. 1, right) uses quantile (octile) classification and the map of raw grid values (Fig. 1, left) uses the same breaks to classify the raw *atlas* light pollution values into eight categories. Note that the *atlas* dataset only gauges artificial brightness (i.e., values that surpassed the 174 μcd/m^2 threshold used to define light pollution). Thus, our dependent variable represents a census tract-level measure of mean ambient light pollution, capturing artificial nighttime radiance values above the 174 μcd/m^2 threshold.

2.3. Independent variables: racial and ethnic composition

Our analysis included variables for the proportions of residents identifying as non-Hispanic Black, Hispanic/Latino, non-Hispanic Asian, non-Hispanic American Indian or Alaskan Native, non-Hispanic Native Hawaiian or Pacific Islander, and non-Hispanic Multi-/other race in each US census tract (we hereafter remove "non-Hispanic" from references to each minority group) (US Census Bureau, 2017a). We excluded the proportion of non-Hispanic White residents from the multivariable models, such that results for the racial/ethnic minority group variables would be interpretable relative to the proportion of tract residents who identified as White. We calculated the proportion variable for each racial/ethnic group by dividing the population count for each group by the total population in each respective census tract.

2.4. Independent variables: socioeconomic status (SES)

To analyze the effect of SES on exposure to light pollution, we included the proportion of renter-occupied housing units (US Census Bureau, 2017b) and median household income (US Census Bureau, 2017c) in our multivariable modelling (addressing our second and third questions). Renter-occupancy status is often included in EJ studies because it represents greater housing instability when compared to owner-occupancy. Additionally, renters often experience decreased political power and lack the resources necessary to reduce their environmental exposures (Pastor et al., 2005). We included median household

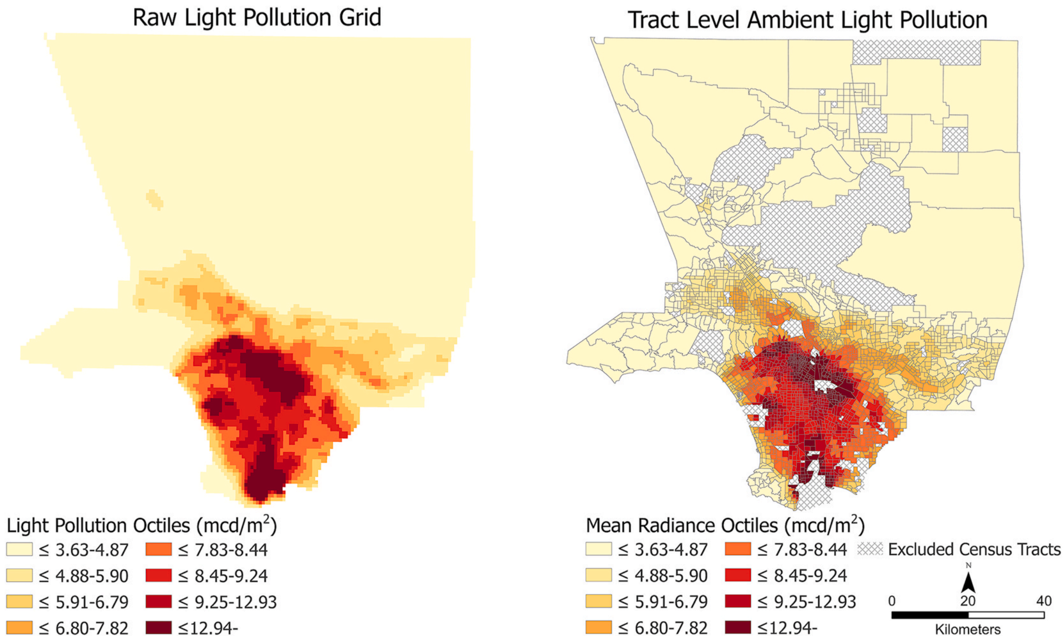

Fig. 1. An example of the zonal statistics operation in Los Angeles County, California. Note: Map on left shows raw radiance grid values. Map on right shows resulting mean radiance values for census tracts. Hatch patterns (right) represent census tracts excluded due to low population counts.

income in our analysis because it pertains directly to wealth, power, and the political influence of a neighborhood. The ACS provides this variable at the census tract level. In our multivariable modelling, we included a median household income squared term to account for the possibility of a curvilinear relationship between hazard exposure and income. Such relationships may be attributed to the fact that lower-income neighborhoods often lack economic activities, and may therefore have fewer sources of light pollution, while higher-income neighborhoods have the resources necessary to protect themselves from sources of acute light pollution. Thus, middle-income neighborhoods may be disproportionately exposed to particular anthropogenic hazards (Collins et al., 2017; Pastor et al., 2005).

2.5. Control variables

Because artificial lighting is concentrated in urban environments, we included variables in our multivariable modelling (addressing our second and third questions) to account for the level of urbanization. We gauged population density by dividing the total tract population by the area of the tract in square kilometers. Additionally, we adjusted for urban effects by defining clusters of tracts within counties based on the age of the housing stock (described below). In our full model (addressing our second question), we also included categorical variables to adjust for the location of tracts along the urban-rural continuum based on the US Department of Agriculture's Rural-Urban Commuting Area (RUCA) primary codes (USDA, 2019). There are 10 codes: code 1 represents metropolitan core contexts, codes 2–3 represent metropolitan area suburban contexts, codes 4–6 represent small city contexts, and codes 7–10 represent small town and rural contexts. Detailed definitions for the RUCA codes are available from the USDA (2019). We excluded RUCA code 1 (i.e., metropolitan core tracts) from the full model and treated it as the reference group because it included the majority of tracts in the analysis; thus, results for all RUCA codes in our full model are interpretable in reference to RUCA code 1. We also used the RUCA codes to define the strata to examine research question 3 (described below).

2.6. Analysis: population-weighted mean exposure to ambient light pollution

To address our first question, we calculated the national population-weighted mean exposure to ambient light pollution at night for each racial/ethnic group, based on population counts for each group in each census tract. We did this by multiplying the total number of people in each racial/ethnic group in each census tract by the mean radiance (ambient light at night) in each respective census tract, and then summing those values across all tracts before dividing by the total US population for each group. Population-weighted mean calculations are used in EJ studies because they clearly describe the actual (unadjusted) environmental exposures for specific demographic groups, allow for the reliable examination of groups with small counts, and create a point of comparison for modelling techniques that include additional variables of relevance (Clark et al., 2014; Collins et al., 2017; Grineski et al., 2017; Rubio et al., 2020).

2.7. Analysis: multivariable generalized estimating equations

We used generalized estimating equations (GEEs) to assess social inequities in light pollution while adjusting for the effects of geographic clustering and other variables. To address our second question, we specified a full model with all continental US census tracts that met our inclusion criteria ($n = 70{,}358$); this GEE included RUCA codes 2–10 as control variables for urban-rural context. To address our third question, we stratified census tracts into three subgroups—metropolitan core tracts (RUCA code 1; $n = 50{,}200$), suburban tracts (RUCA codes 2–3; $n = 7333$), and small city–rural tracts (RUCA codes 4–10; $n = 12{,}825$)—and then specified separate GEEs for each subgroup. Other national EJ analyses have applied similar census tract stratification approaches based on RUCA codes (e.g., Bravo et al., 2016).

GEEs extend the generalized linear model to accommodate clustered and non-normally distributed data (Liang and Zeger, 1986). For our full and subgroup models, we defined clusters of census tracts based on the median year of housing construction category (i.e., "2000 or later", "1990 to 1999", "1980 to 1989", "1970 to 1979", "1960 to 1969", "1950 to 1959", "1940 to 1949", and "1939 or earlier") by county, which led to a total of 10,537 clusters. We selected this cluster definition because it corresponds with the residential development contexts wherein census tracts are nested; e.g, within older central cities vs. newer urban fringe areas, which differ in terms of light pollution. Additionally, this cluster definition is appropriate because it relates to the historical and geographical formation of environmental injustices. For example, in many parts of the US, institutional racism in housing and urban development have influenced minority groups to experience concentrated poverty in older central city neighborhoods, and enabled privileged Whites to pursue affluent lifestyles in newer housing developments along the expanding urban fringe (Bolin et al., 2005; Davis, 2006; Pulido, 2000). Several recent distributive EJ studies have used this cluster definition based on similar logic (Collins et al., 2017, 2019b, 2020).

GEEs require the specification of an intracluster dependency correlation matrix, a distribution, and a link function (Liang and Zeger, 1986). Three correlation matrix specifications were potentially appropriate: independent, exchangeable, and unstructured. Based on the distributions of the variables, three GEE distributions and two link functions were candidates: normal, gamma, inverse Gaussian or Tweedie (index parameter = 1.5; i.e., compound Poisson-gamma) distributions, with identity or logarithmic (log) link functions. We estimated a series of GEEs using the independent variables to predict artificial light at night using all possible combinations of those correlation matrices, distributions, and link functions. We then used quasi-likelihood under the independence model criterion (QIC) goodness-of-fit measures to determine the best fitting specification. For the full model, an unstructured correlation matrix with a gamma distribution and log link function fit best. The best fitting specification for the metropolitan core subgroup model was an unstructured correlation matrix, inverse Gaussian distribution, and log link function. For the suburban subgroup model, the best fitting specification was an unstructured correlation matrix, normal distribution, and identity link function. For the small city–rural subgroup model, an exchangeable correlation matrix, normal distribution, and identity link function was best fitting. Note that comparison of effect sizes for specific coefficients between the four models is not permissible, due to the different model specifications.

To assess multicollinearity among the analysis variables, we examined the variance inflation factor, tolerance, and condition index; these values indicated that inferences from all GEEs were unaffected by multicollinearity. We standardized all continuous independent variables before including them in GEEs to make coefficients directly comparable within each model. We define statistical significance as $p < 0.05$. We used IBM SPSS Statistics version 23 to conduct the statistical analyses (IBM, 2015).

3. Results

3.1. Descriptive analytics

We present descriptive statistics for all variables in Table 1. Fig. 2 depicts the spatial distribution of artificial light across continental US census tracts. Light pollution is most apparent in the heavily urbanized northeastern portion of the country. Additionally, zones of high artificial light at night appear along the west coast. While some areas of high artificial light at night are present in the central portions of the US, particularly in urbanized areas to the east, the west-central portion of the country is generally darker than the coastlines. Fig. 3 depicts the spatial distributions of the race/ethnicity and SES independent variables. The geographic distributions of each of the racial/ethnic groups indicate regional patterns of representation. While the distributions of the SES variables appear less regionally patterned, metropolitan areas included tracts with relatively high median household incomes (Fig. 3).

3.2. Population-weighted mean exposure to ambient light at night

Fig. 4 reports the results for the analysis of population-weighted mean exposure to ambient light at night in mcd/m^2, addressing our first question. Each racial/ethnic group, along with the national average, is listed in rank order from high-to-low for mean exposure to ambient light at night. Asians had the highest population-weighted mean exposure to ambient light pollution (4.134 mcd/m^2), followed by Hispanics (3.988), Blacks (3.970) and Native Hawaiian/Pacific Islanders (3.061). American Indian/Alaskan Natives had the lowest population-weighted mean levels of exposure (1.371 mcd/m^2), followed by the Multi-/other race group (1.498), and Whites (2.000).

Given that the national average for population-weighted mean exposure to ambient light at night was 2.703 mcd/m^2, Asians, Hispanics, Blacks, and Native Hawaiian/Pacific Islanders respectively had 52.9%, 47.5%, 46.9%, and 13.24% higher than average levels of exposure. Most groups also exhibited a higher risk for exposure to ambient light pollution when compared to the Whites specifically. For example, exposure levels for Asians, Hispanics, Blacks, Native Hawaiian/Pacific Islanders were respectively 106.7%, 99.4%, 98.5%, and 53.1% higher than the population-weighted mean exposure for Whites. Only American Indian/Alaskan Natives and those of Multi-/other race had lower population-weighted mean exposures than Whites.

Table 1
Descriptive statistics for variables analyzed, continental United States census tracts (n = 70,358).

Continuous Variables	Min.	Max.	Mean	St. Dev.
Mean Radiance (mcd/m^2)	0.0003	33.973	2.813	2.922
Proportion Black	0.00	1.00	0.135	0.218
Proportion Hispanic	0.00	1.00	0.157	0.209
Proportion Asian	0.00	0.91	0.045	0.085
Proportion AIAN	0.00	1.00	0.007	0.043
Proportion NHPI	0.00	0.17	0.001	0.005
Proportion Multi-/Other Race	0.00	0.43	0.024	0.026
Proportion White	0.00	1.00	0.630	0.299
Proportion Renter	0.00	1.00	0.370	0.227
Median Household Income (2016 US$)	3250	249,597	58,898	29,052
Population Density (people/km^2)	0.219	508,697	5224	11,803
Dichotomous Variables	**Min.**	**Max.**	**No (0)**	**Yes (1)**
RUCA Code 1	0	1	20,158	50,200
RUCA Code 2	0	1	63,675	6683
RUCA Code 3	0	1	69,708	650
RUCA Code 4	0	1	66,217	4141
RUCA Code 5	0	1	68,409	1949
RUCA Code 6	0	1	69,950	408
RUCA Code 7	0	1	68,236	2122
RUCA Code 8	0	1	69,541	817
RUCA Code 9	0	1	70,017	341
RUCA Code 10	0	1	67,311	3047

Note: AIAN = American Indian or Alaska Native; NHPI = Native Hawaiian or Pacific Islander.

3.3. Full multivariable model predicting neighborhood-level ambient light at night

Table 2 reports the results of the GEE predicting exposure to light pollution across US census tracts, addressing our second question. Results in the Exp(B) column, after subtracting one and multiplying by 100, are interpretable as the percentage change in exposure to ambient light at night per one standard deviation increase in each of the independent variables. Results for the race/ethnicity variables generally indicate greater exposure to light at night. Specifically, one standard deviation increases in the proportions of Black, Hispanic, Asian, and Multi-/other race residents in census tracts were respectively associated with 20.9%, 15.0%, 8.1%, and 1.2% increases to ambient light at night ($p < 0.01$). As an exception, an increase in the proportion of Native Hawaiian/Pacific Islander residents was associated with a small but significant decrease in ambient light at night ($p < 0.01$).

We found that an increase in the proportion of renter-occupants within census tracts was associated with significantly greater light

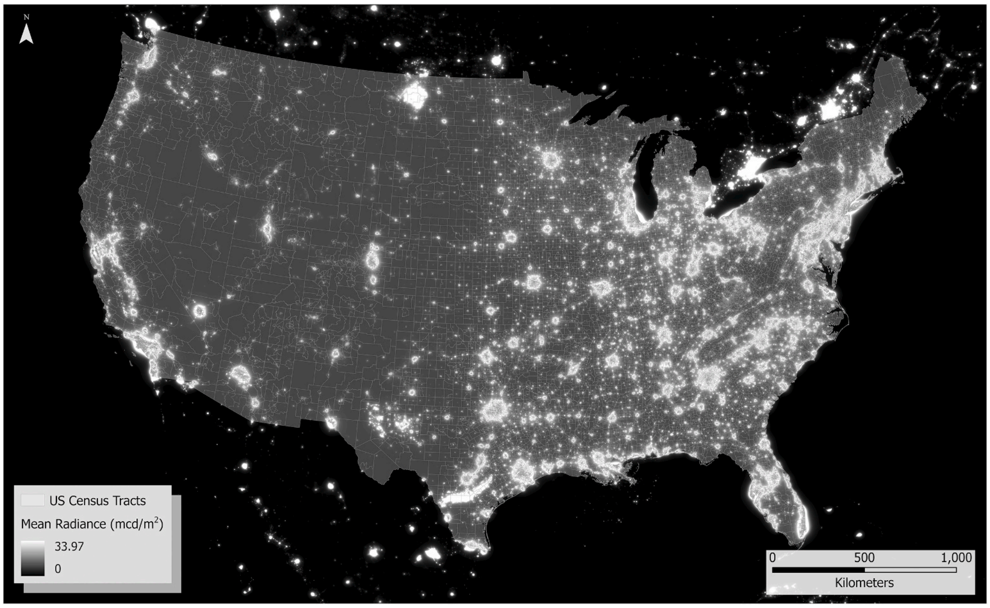

Fig. 2. The spatial distribution of ambient light pollution across continental United States census tracts. Data Source: Falchi et al. (2016b).

pollution, such that a one standard deviation increase in the tract proportion of renter-occupants was associated with a 38.8% increase in the level of ambient light at night ($p < 0.001$). We also found that median household income was a significant nonlinear predictor of exposure to artificial light at night, whereby lower and higher levels of income at the census tract level were associated with lower levels of light pollution and middle levels of income were associated with increased exposure to ambient light at night ($p < 0.001$). In terms of the inflection point, the curve starts to descend (indicating lowering light pollution) past approximately $70,000 median household income.

Increases in population density were associated with greater ambient light at night ($p < 0.001$). Additionally, when compared to tracts located in metropolitan core areas (i.e., RUCA code 1), those in less urbanized contexts (RUCA codes 2–10) were associated with large decreases in the level of artificial light at night ($p < 0.001$).

3.4. *Stratified multivariable models predicting neighborhood-level ambient light at night*

Table 3 reports the results for the metropolitan core, suburban, and small city–rural subgroup GEEs, which address our third question. In metropolitan core neighborhoods, one standard deviation increases in the proportions of Black, Hispanic, and Asian residents were respectively associated with 21.8%, 13.9% and 13.6% increases in ambient light pollution ($p < 0.001$). A one standard deviation increase to the proportion of Native Hawaiian/Pacific Islander residents was associated with a 1.2% decrease in ambient light at night ($p < 0.01$). In terms of SES, we found that a one standard deviation increase in tract-level renter-occupancy in metropolitan core areas was associated with a 17.1% increase in artificial light at night ($p < 0.001$). Median household income was positively and linearly related to ambient light such that a one standard deviation increase was associated with a 11.2% increase in light ($p < 0.001$).

In the suburban model, one standard deviation increases in the proportions of Black, Hispanic, and Asian residents were respectively associated with 0.085, 0.045 and 0.198 mcd/m^2 increases in artificial light at night ($p < 0.001$). In terms of SES, a one standard deviation increase in renter-occupancy was associated with a 0.084 mcd/m^2 increase in ambient light pollution ($p < 0.001$). Median household income followed a similar significant and curvilinear relationship with artificial light ($p < 0.01$) to that exhibited in the full model.

In our small city–rural model, we found that one standard deviation increases in the proportions of Black, Asian, and Multi-/other race residents were respectively associated with 0.087, 0.081, and 0.008 mcd/m^2 increases in ambient light pollution ($p < 0.01$). A one standard deviation increase in the proportion of American Indian/Alaskan Native residents was associated with a 0.004 mcd/m^2 decrease in artificial light ($p < 0.01$). For SES, we found that a one standard deviation increase in tract-level renter-occupancy in small city–rural environments was associated with a 0.167 mcd/m^2 increase in artificial light at night ($p < 0.001$). A one standard deviation increase in median household income was positively and linearly associated with a 0.100 mcd/m^2 increase in light ($p < 0.01$).

4. Discussion

Our results reveal socially disparate patterns of residential exposure to ambient light at night, which is an important finding given that this was the first EJ analysis of light pollution. The population-weighted mean analysis, which did not adjust for the effects of geographic clustering or other variables, indicated that, in rank order, Asians, Hispanics, Blacks, and Native Hawaiian/Pacific Islanders in the US experienced substantially greater neighborhood exposures to ambient light at night than Whites. In terms of our multivariable GEEs, we found that higher proportions of Black or Asian residents were associated with significantly higher levels of artificial light at night across all US census tracts, and in metropolitan core, suburban and small city–rural strata. Higher proportions of Hispanic residents were positively associated with light in all four models and the associations were significant in the full, metropolitan core and suburban models. Those findings generally align with EJ studies examining air and road transportation noise (Collins et al., 2020) and air pollution (Grineski et al., 2017). The consistent findings for the Black, Asian and Hispanic neighborhood composition variables across the bivariate models and the GEEs are of particular importance, as they suggest that disparities in exposure to artificial light across the continental US may be related more to racial/ethnic status than geographic context.

Unlike Black, Asian and Hispanic populations, Native Hawaiian/Pacific Islander and American Indian/Alaskan Native groups were generally less exposed to light than White Americans in the GEE models. This trend was statistically significant based on Native Hawaiian/Pacific Islander neighborhood composition in metropolitan core areas and in all

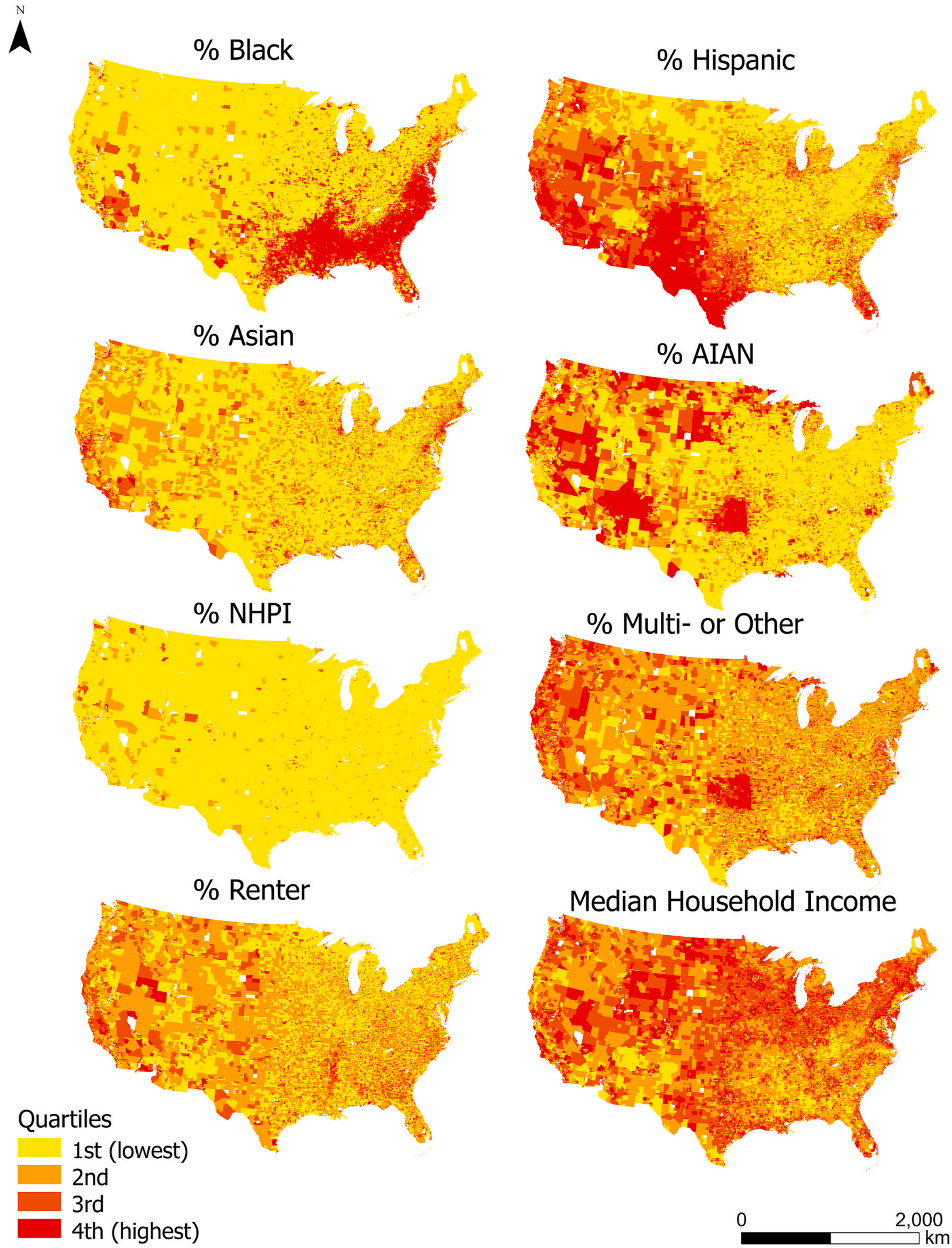

Fig. 3. The spatial distribution of sociodemographic analysis variables across continental United States census tracts (n = 70,358). Note: AIAN = American Indian or Alaska Native; NHPI = Native Hawaiian or Pacific Islander.

US tracts, even though their unadjusted, population-weighted mean light pollution exposure was above the national average. We found that the American Indian/Alaskan Native group was significantly protected from light pollution in rural neighborhoods. They also had the lowest population-weighted mean light pollution exposure of all groups examined. This finding may reflect how American Indian/Alaska Native communities have been marginalized within geographically isolated and less economically productive rural landscapes, characterized by relatively low per capita levels of energy consumption and darker skies (Coscieme et al., 2014).

In terms of SES, the neighborhood prevalence of renter-occupants was positively and significantly associated with increased ambient light pollution, regardless of where a tract was located along the urban-rural continuum. The renter-occupancy finding generally aligns with EJ analyses of other hazards in the US. For example, Collins et al. (2020) found that air and road transportation noise had disparate impacts based

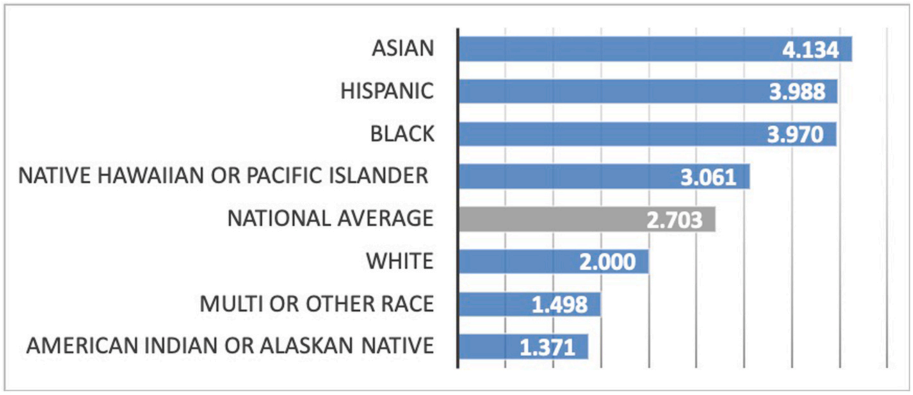

Fig. 4. Population-weighted mean exposure to ambient light pollution for racial/ethnic groups in the continental United States in mcd/m^2 (n = 310,323,507 people).

Table 2
Results of generalized estimating equation predicting ambient light pollution for continental United States census tracts (n = 70,358).

Parameter	Beta	Exp(B)	95% CI	*p*-value
Intercept	0.974	2.647	0.946, 1.002	<0.001
Proportion Black	0.190	1.209	0.176, 0.203	<0.001
Proportion Hispanic	0.140	1.150	0.122, 0.157	<0.001
Proportion Asian	0.078	1.081	0.067, 0.089	<0.001
Proportion AIAN	−0.020	0.981	−0.046, 0.007	0.153
Proportion NHPI	−0.009	0.991	−0.016, −0.003	0.005
Proportion Multi-/Other Race	0.012	1.012	0.004, 0.020	0.003
Proportion Renter	0.251	1.286	0.231, 0.272	<0.001
Med. Household Income	0.280	1.323	0.237, 0.323	<0.001
Med. Household Income Sq.	−0.113	0.893	−0.144, −0.082	<0.001
Population Density	0.180	1.197	0.151, 0.208	<0.001
RUCA Code 2	−1.555	0.211	−1.619, −1.492	<0.001
RUCA Code 3	−2.166	0.115	−2.248, −2.084	<0.001
RUCA Code 4	−1.130	0.323	−1.174, −1.086	<0.001
RUCA Code 5	−2.358	0.095	−2.419, −2.297	<0.001
RUCA Code 6	−2.325	0.098	−2.432, −2.219	<0.001
RUCA Code 7	−1.950	0.142	−2.001, −1.899	<0.001
RUCA Code 8	−2.864	0.057	−2.940, −2.788	<0.001
RUCA Code 9	−2.577	0.076	−2.656, −2.498	<0.001
RUCA Code 10	−3.002	0.050	−3.074, −2.930	<0.001

Note: AIAN = American Indian or Alaska Native; NHPI = Native Hawaiian or Pacific Islander. All continuous predictors were standardized. The model uses an unstructured correlation matrix, gamma distribution, and logarithmic link function, and adjusts for clustering by county and age of housing stock. Racial/ethnic minority group variables are interpretable in reference to the proportion of White residents. RUCA codes 2–10 are interpretable in reference to RUCA code 1 (metropolitan core).

on renter-occupancy across US census tracts.

We found a curvilinear relationship between neighborhood median household income and ambient light pollution in the full and suburban models. Other EJ studies found something similar whereby middle-income neighborhoods shouldered the greatest exposures to hazardous waste and air pollution (Boer et al., 1997; Chakraborty et al., 2014; Morello-Frosch et al., 2001). The dip in light pollution we found at high-income levels is likely due to the location of exclusive, affluent enclaves (e.g., master-planned communities), outside of central cities on the darker metropolitan fringes, within suburban/exurban contexts. In metropolitan core and small city–rural tracts, the pattern differed such that greater income linearly predicted increasing ambient nighttime light, which we did not expect based on the EJ literature. A separate literature using remote sensing-based measures, however, has associated greater nighttime light with increased population density, greater wealth and economic activity, less poverty, and increased nonrenewable energy consumption at coarse spatial scales (Coscieme et al., 2014; Elvidge et al., 2009, 2012; Ghosh et al., 2010; Sutton et al., 1997). Given that our models adjust for population density and renter-occupancy, our finding in metropolitan core contexts may be attributable to increased economic activity and energy consumption in and around higher-income central city neighborhoods as well as the prevalence of relatively high income renter-occupants in specific high-light residential settings (e.g., in downtown multi-unit complexes). In small city–rural contexts, our finding was likely influenced by increased economic activity in higher-income neighborhoods nearer to town centers as well as higher poverty rates and reduced per capita energy consumption (e.g., from a lack of public street lighting) in more isolated, lower-income rural settings. While our findings across the urban-rural strata were remarkably similar, distinctions such as those based on income are important because they suggest the role of geographic context in moderating particular social-light pollution relationships.

There are several possible explanations for the light pollution inequities we found. First, the US-based EJ literature has documented a concentration of residentially undesirable land use activities, which often emit high levels of artificial light at night, within Black, Hispanic and Asian communities (Pais et al., 2013; Cutter, 1995; Bullard, 2000; Grineski et al., 2017). Second, as artificial nighttime light becomes increasingly undesirable, darkness emerges as an environmental amenity, and desires to promote darker skies become more influential in planning initiatives (City of Los Angeles, 2009; Daley, 2007, 2010; Mikyoung, 2008; Newell et al., 2013), privileged rather than socially disadvantaged neighborhoods are more likely to experience darkened nights. Our results indicate that neighborhoods with high rates of owner-occupancy experience darker nights than those with a high prevalence of renter-occupants, likely due to the collective power of homeowners to repel sources of acute light pollution from their neighborhoods (Pastor et al., 2005). We also presume that our nonlinear findings for reduced light pollution at the higher-end of the income distribution (esp. in suburban areas) are suggestive of a trend that will accentuate in the future, given the increasing social desirability of dark nights. Third, the criminalization of particular US racial/ethnic minority groups (e.g., Black and Hispanic Americans) and efforts to control their populations through urban design (Davis, 2006; Gomberg-Muñoz, 2012; Muhammad, 2019)—specifically through the deployment of artificial lighting to facilitate nighttime policing and surveillance by law enforcement authorities—may also explain disparities in exposure to light pollution.

The disparities we identified in neighborhood exposure to ambient light at night may foster improved understanding of health disparities across the US. Because light pollution has well-established links with human health problems—including sleep impairment (Pauley, 2004; Raap et al., 2015), sleep-deficiency related issues such as diabetes (Mokdad et al., 2003), gastrointestinal disorders (Delgado-Aros et al., 2004; Donhoe et al., 2010), cardiovascular disease (Eckel et al., 1998; Zhou et al., 2000), and various forms of cancer (Davis et al., 2001; Hansen, 2001; Kloog et al., 2010)—future research should seek to

Table 3
Results of generalized estimating equations predicting ambient light pollution in metropolitan core, suburban, and small city–rural census tracts of the continental United States.

Parameter	Metropolitan Core n = 50,200				Suburban n = 7333			Small City–Rural n = 12,825		
	Beta	Exp(B)	95% CI	*p-value*	Beta	95% CI	*p-value*	Beta	95% CI	*p*-value
Intercept	1.273	3.570	1.248, 1.297	<0.001	1.644	1.407, 1.882	<0.001	1.330	1.232, 1.428	<0.001
Proportion Black	0.197	1.218	0.185, 0.210	<0.001	0.085	0.064, 0.106	<0.001	0.087	0.073, 0.101	<0.001
Proportion Hispanic	0.130	1.139	0.107, 0.153	<0.001	0.045	0.022, 0.068	<0.001	0.007	−0.005, 0.019	0.243
Proportion Asian	0.128	1.136	0.113, 0.143	<0.001	0.198	0.123, 0.272	<0.001	0.081	0.035, 0.128	0.001
Proportion AIAN	−0.034	0.966	−0.070, 0.001	0.058	−0.002	−0.006, 0.001	0.195	−0.004	−0.007, −0.001	0.006
Proportion NHPI	−0.012	0.988	−0.020, −0.004	0.004	−0.013	−0.032, 0.006	0.180	−0.005	−0.013, 0.003	0.198
Proportion Multi-/Other Race	0.001	1.001	−0.009, 0.012	0.806	0.004	−0.007, 0.014	0.491	0.008	0.002, 0.015	0.010
Proportion Renter	0.158	1.171	0.140, 0.176	<0.001	0.084	0.049, 0.118	<0.001	0.167	0.150, 0.183	<0.001
Median Household Income	0.106	1.112	0.063, 0.150	<0.001	0.239	0.174, 0.303	<0.001	0.100	0.026, 0.174	0.008
Median Household Income Sq.	0.003	1.003	−0.028, 0.034	0.854	−0.103	−0.171, −0.035	0.003	−0.052	−0.171, 0.067	0.393
Population Density	1.962	7.112	1.882, 2.042	<0.001	2.632	2.072, 3.192	<0.001	2.166	1.937, 2.396	<0.001

Note: AIAN = American Indian or Alaska Native; NHPI = Native Hawaiian or Pacific Islander. All continuous predictors were standardized. Each model adjusts for clustering by county and age of housing stock. The metropolitan core model uses an unstructured correlation matrix, inverse Gaussian distribution, and logarithmic link function; a Exp(B) column including exponentiated parameter estimates is included to aid interpretation. The suburban model uses an unstructured correlation matrix, normal distribution, and identity link function. The rural model uses an exchangeable correlation matrix, normal distribution, and identity link function. Exp (B) columns are not provided for the suburban or rural models as logarithmic link functions are not utilized. Racial/ethnic minority group variables are interpretable in reference to the proportion of White residents.

determine whether inequitable exposures to artificial light at night influence and interact with the health disparities experienced by racial/ethnic minority and economically-disadvantaged populations in the US. For example, the incidence rate of prostate cancer is disproportionately high among Black males (Powell, 2007; Tsodikov e al., 2017), such that they have a risk of diagnosis that is 1.7 times higher than their White male counterparts (Brawley, 2012). Additionally, prostate cancer mortality rates are 2.3 times greater among Black men than White men residing in the US (Brawley, 2012). African American women experience similar health disparities, with their breast cancer incidence rates increasing while those for White women have remained stable (DeSantis et al., 2017). They are also more likely to develop high-risk breast tumors that are less receptive to modern treatments when compared to their White counterparts (Dunn et al., 2010). Those disparities in cancer diagnosis and prognosis—particularly in regard to cancers associated with light pollution—suggest that socially inequitable exposures to artificial light may play some role in extant health disparities in the US. To improve understanding, it will be important for future studies to assess to the role of uneven exposure to ambient light at night as an influence on disparate population-level health outcomes.

Our findings raise concerns about a multiple environmental jeopardy situation, wherein racial/ethnic minority and economically deprived communities experience compounding impacts from multiple environmental hazards. Exposures to multiple hazards threaten community health and wellbeing, such that inequitable exposures to light at night may interact with unequal exposures to other hazards, like air pollution, noise, and substandard housing. In such cases, the deleterious human effects of other environmental exposures—such as increased risk for cancer (Chakraborty et al., 2017) and diabetes (Dendup et al., 2018), or impaired academic performance (Grineski et al., 2020)—might be magnified by disparate exposures to light pollution.

Our analysis has several limitations. It was cross-sectional, which limited our ability to understand how disparities in exposure to ambient light pollution in the US may have developed or changed over time. While cross-sectional analyses are useful in identifying patterns—especially in the context of light pollution, which has not previously been examined from an EJ perspective—it will be important for future research to clarify explanations of light pollution disparities through historical or longitudinal analyses of specific US cities or regions. Additionally, all currently available global low-light imaging data used in light pollution analyses are blind in the blue range of the visible light spectrum. This means that the VIIRs DNB measurements of lighting used in this analysis may underestimate the severity of ambient light pollution. The VIIRs DNB sensor also does not account for the attenuation of light pollution that may occur due to quality of residential structures or indoor behaviors with respect to artificial light at night. We acknowledge that our measurement of ambient light at night does not serve as a proxy for all forms of individual exposure to light pollution, and future research would benefit from examining social disparities in exposure to light pollution with individual-level data that account for multiple forms of exposure. Nevertheless, the estimates of ambient light at night we employed were the best available for the US and they are of a finer spatial resolution than the estimates used in prior health analyses of exposure to ambient light pollution.

5. Conclusions

This was the first distributive EJ analysis of exposure to artificial light at night. It utilized the best available estimates of light pollution across the continental US, and empirically documented a pattern whereby neighborhoods with higher proportions of Black, Hispanic and Asian residents and renter-occupants were exposed to greater ambient light at night across the urban-rural continuum. Our results generally align with findings from EJ analyses of other anthropogenic hazards. Continued research on the EJ implications of light pollution should seek to identify the processes responsible for the disparities we documented, as a complete understanding of both the drivers and repercussions of disparate exposures to ambient light at night will be needed to identify appropriate solutions.

Given that neighborhoods composed of racial/ethnic minority and renter-occupant populations are disproportionately burdened by ambient light at night in the US—and that the impacts of light pollution will worsen in terms of luminosity and geographic extent (Kyba et al., 2017)—policy actions are needed. Municipal governments should consider adopting the use of warm-colored LED bulbs, as they are less harmful to human health than cool-colored bulbs, but equally energy efficient (Falchi et al., 2016a). Additionally, motion sensors, timers, and directional filters can be installed to public lightning fixtures to ensure that light is emitted only when and where it is required by human activity. Such practicable steps would have immediate impacts on the levels of ambient light present at night in communities and would likely help to mitigate disparities in exposure to light pollution. Efforts taken to reduce light pollution in communities should also seek to incorporate the voices of residents who prefer higher levels of light at night in particular spaces. While the reduction of light levels has the potential to improve the health and wellbeing of an entire community, artificial lighting in areas such as transportation corridors or residential zones may promote a sense of safety for some residents. In order to balance the needs of diverse neighborhoods, a range of perspectives must be included in the process of creating and employing solutions.

On a broader scale, land use and housing policy processes in the US must be engaged in order to address the disparities we documented. Policies and practices of the past and present have played a role in concentrating light pollution and its accompanying health risks within neighborhoods comprised of relatively high proportions of racial/ethnic minorities and renter-occupant households. Future housing and land use policies in the US should seek to increase affordable housing options for socially disadvantaged populations within areas not impacted by acute light pollution. A wider range of affordable housing options would likely decrease the disparities in exposures to light pollution and other environmental hazards observed across the US. Additionally, zoning regulations limiting the amount of night light emitted by industrial or commercial activities, as well as restricting the construction of new residential developments in zones designated for light-intensive activities, may also help redress environmental injustices associated with light pollution. Federal agencies are mandated to pursue EJ in equitably protecting the health and wellbeing of all US communities (Clinton, 1994). In order to achieve that mandate, disparities in exposure to ambient light pollution should be considered. It is our hope that this study contributes to the recognition of and efforts to address light pollution inequities across US communities.

CRedit author statement

SMN: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft, Writing - Review & Editing, Visualization. TWC: Methodology, Writing - Review & Editing, Supervision. SEG: Writing - Review & Editing, Supervision.

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Declaration of competing interest

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

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