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Racial, Ethnic, and Socioeconomic Disparities in Multiple Measures of Blue and Green Spaces in the United States

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Background: Several studies have evaluated whether the distribution of natural environments differs between marginalized and privileged neighborhoods. However, most studies restricted their analyses to a single or handful of cities and used different natural environment measures.

Objectives: We evaluated whether natural environments are inequitably distributed based on socioeconomic status (SES) and race/ethnicity in the contiguous United States.

Methods: We obtained SES and race/ethnicity data (2015–2019) for all U.S. Census tracts. For each tract, we calculated the Normalized Different Vegetation Index (NDVI) for 2020, NatureScore (a proprietary measure of the quantity and quality of natural elements) for 2019, park cover for 2020, and blue space for 1984–2018. We used generalized additive models with adjustment for potential confounders and spatial autocorrelation to evaluate associations of SES and race/ethnicity with NDVI, NatureScore, park cover, and odds of containing blue space in all tracts ($n = 71{,}532$) and in urban tracts ($n = 45{,}338$). To compare effect estimates, we standardized NDVI, NatureScore, and park cover so that beta coefficients presented a percentage increase or decrease of the standard deviation (SD).

Results: Tracts with higher SES had higher NDVI, NatureScore, park cover, and odds of containing blue space. For example, urban tracts in the highest median household income quintile had higher NDVI [44.8% of the SD (95% CI: 42.8, 46.8)] and park cover [16.2% of the SD (95% CI: 13.5, 19.0)] compared with urban tracts in the lowest median household income quintile. Across all tracts, a lower percentage of non-Hispanic White individuals and a higher percentage of Hispanic individuals were associated with lower NDVI and NatureScore. In urban tracts, we observed weak positive associations between percentage non-Hispanic Black and NDVI, NatureScore, and park cover; we did not find any clear associations for percentage Hispanics.

Discussion: Multiple facets of the natural environment are inequitably distributed in the contiguous United States. https://doi.org/10.1289/EHP11164

Introduction

Of all high- and middle-income countries, the United States has among the highest income-related disparities in self-reported health and health care measures.[1] Health disparities have been attributed to several factors, such as health behaviors, housing conditions, and access to health care.[2,3] Recently, increasing attention has been paid to the role of environmental exposures.[4,5] Research suggests that exposure to natural environments (e.g., green space, parks, and blue space) may protect against several adverse health outcomes, including depression,[6–9] cardiovascular disease,[6,9,10] and mortality.[6–10] Protective associations of green space are generally stronger for low-socioeconomic status (SES) individuals than for individuals in more affluent groups.[4] Therefore, an inequitable distribution of natural environments could partially explain the observed health disparities.

Several studies have evaluated whether the distribution of green and blue spaces differs between marginalized and privileged neighborhoods.[5,11–13] A meta-analysis reported that higher income households or neighborhoods have more urban forest cover than lower income households or neighborhoods.[12] A review showed that marginalized neighborhoods have access to fewer acres of parks and have parks with lower quality than more privileged neighborhoods but found mixed results for park proximity.[11] Results for differences in natural environment measures between race/ethnic groups are less clear. Another review reported significant race-based inequity in urban forest cover, but this inequity disappeared when only studies that adjusted for income were included.[13]

Most studies included in natural environment–inequity reviews restricted their analyses to a single or handful of cities, used a wide range of different constructs to quantify SES or race/ethnicity, and differed in their control for potential confounders.[5,11–13] This may have led to differences in associations between studies and limits the generalizability of the results. Moreover, two studies showed that patterns of natural environment inequity varied by measure of the natural environment considered.[14,15] Different measures of the natural environment (e.g., greenness, parks, or tree cover) capture different aspects of the natural environment that may result in differing associations between studies. For example, the Normalized Difference Vegetation Index (NDVI) captures private greenery (backyards) and could therefore be more strongly related to SES measures than parks. To the best of our knowledge, there is no study that covers the entire contiguous United States and compares diverse natural environment measures to assess whether natural environments vary by SES and race/ethnicity.

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Our aim was to evaluate whether natural environments were inequitably distributed by U.S. Census tract SES and race/ethnicity in the contiguous United States. We analyzed whether median household income, percentage of households below the U.S. poverty level, percentage of the population with less than a high school education (%<high school education), %non-Hispanic White and Black, and %Hispanic across all census tracts were associated with several measures capturing different aspects of the natural environment. To compare findings between all and urban tracts, we additionally analyzed associations in all urban tracts ($\geq$1,000 persons/mi^2) in the contiguous United States.

Methods

SES and Race/Ethnicity

We downloaded data on several SES indicators and race/ethnicity for each census tract in the contiguous United States from the National Historical Geographic Information System (https://www.nhgis.org).[16] Census tracts are small, relatively permanent statistical subdivisions of the United States with an average population size of between 1,200 and 8,000 people.[17] The spatial size of the tracts varies widely depending on the density of the settlement. For each tract, we obtained SES indicators and racial/ethnic composition from the 2015–2019 American Community Survey (ACS), which is a nationwide survey and has an annual sample size of about 3.5 million addresses.[18] The U.S. Census Bureau combines 5 consecutive years of ACS data to produce more reliable and precise estimates, especially for small geographic areas and small population subgroups.

Given that SES has multiple components and that associations with measures of the natural environment may differ between SES components, we examined three indicators in our analyses. Specifically, we examined *a*) median household income in the past 12 months (in 2019 inflation-adjusted U.S. dollars), *b*) percentage of households with an income in the past 12 months below the poverty level, and *c*) percentage of the population $\geq$25 years of age with <high school education. Further, we examined the percentages of non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and non-Hispanic people of other races (American Indian and Alaska Native, Native Hawaiian and Other Pacific Islander, some other race, or two or more races) and Hispanic individuals in each tract. Using R (Version 1.2.5042, R Development Core Team), we plotted the spatial variation of the SES and race/ethnicity indicators across the contiguous United States (Figure S1).

Natural Environment Measures

We considered four natural environment measures: *a*) NDVI (an indicator of greenness), *b*) NatureScore (a proprietary measure of the quantity and quality of natural elements), *c*) park cover, and *d*) blue space. We selected these measures because they (or similar measures) have been studied in previous natural environment–inequity studies,[4,5,12,13] capture different aspects/pathways of the natural environment that may be relevant to health, or may protect against adverse health outcomes.[7,8,19,20] These measures vary across the contiguous United States and within cities. Using Google Earth Engine,[22] we created detailed maps of the metropolitan areas of Boston, Massachusetts, Washington, DC, and San Francisco, California (Figure 1). Using R, we plotted the spatial variation of tract-level NDVI, NatureScore, park cover, and blue space (tract + 100-m buffer) in the contiguous United States (Figure S2).

Normalized Different Vegetation Index. We estimated the NDVI, an indicator of greenness, using satellite imagery. NDVI is the ratio between the red and near infrared values, and values range from –1 to 1.[21] Values close to 1 correspond to areas with complete coverage by live vegetation, values close to zero correspond to areas without much live vegetation (e.g., rocks, sand), and negative values correspond to water/ice/snow. We used Landsat 8 images (Collection 1 Tier 1 DN values, representing scaled values, calibrated at sensor radiance) from June 1 through 31 August 2020, to maximize variability in NDVI values. Landsat 8 images are generated every 16 d at a 30-m^2 spatial resolution. Using Google Earth Engine,[22] we created cloud-free Landsat composites for the United States. We calculated the mean summer NDVI for each tract in the contiguous United States by averaging all pixel values in the tract polygons, after setting negative NDVI values to zero. In addition, we used Landsat 8 images from January 1 through 31 December 2020, to calculate the annual average NDVI for each tract in the contiguous United States.

NatureScore. NatureScore is a proprietary measure of the quantity and quality of natural elements and was created by NatureQuant.[23,24] NatureScore is a blend of park space, open water, park features, tree canopy, computer vision (aerial and street view analysis), noise, air pollution, light pollution, human modifications (road densities and impervious surfaces), geographic information system and land classification databases, and satellite infrared vegetation measurements.[23,24] These elements are weighted to create the highest correlation with observed health measures of given natural elements using a proprietary machine learning algorithm.[23,24] The NatureScore values range from 0 (poor NatureScore, lacking beneficial natural elements) to 100 (high NatureScore, abundant beneficial natural elements). The data used in this study were based on calendar year 2019 averages. Each tract's NatureScore was based on a combination of raster (predominantly 10-m^2 spatial resolution) and vector data that fell within the tract boundary.

Park cover. Park cover was based on the U.S. Geological Survey (USGS) Protected Areas Database of the United States (PAD-US). The PAD-US compiles the "best available" data provided by land managing agencies and organizations, and strives to be a complete inventory of public land and other protected areas in the United States.[25] PAD-US differentiates between multiple types of public lands. Therefore, we retrieved polygon data from PAD-US (version 2.1; 2020) and selected land types likely to be known and used by the general public for outdoor recreation to create a park cover data set. This included open and restricted access areas but not closed access areas, therein providing a recreational and accessible version of the PAD-US (i.e., PAD-US-RA). An overview of the included land types can be found in the Supplemental Material in the section "Park cover." To assess park cover, we converted the park data set to a raster image with a spatial resolution of <2 m^2 and calculated park cover (area park/area census tract) for each tract using Google Earth Engine.[22]

Blue space. We estimated blue space using satellite imagery based on the European Commision's Joint Research Centre's Global Surface Water data set.[26] This data set contains maps of the location and temporal distribution of surface water from 1984 to 2018 based on imagery from Landsat 5, 7, and 8 satellites at a 30-m^2 spatial resolution. Surface water data was aggregated over the entire time period and not available for each year. Using Google Earth Engine,[22] we selected the Occurrence band (the frequency with which water was present). If water was present in a pixel for $\geq$50% of the time, we classified the pixel as blue space. If water was present in a pixel for <50% of the time, we classified the pixel as no blue space. Because adjacent water bodies, such as lakes, rivers, and oceans, are not always included within tract boundaries, we calculated the

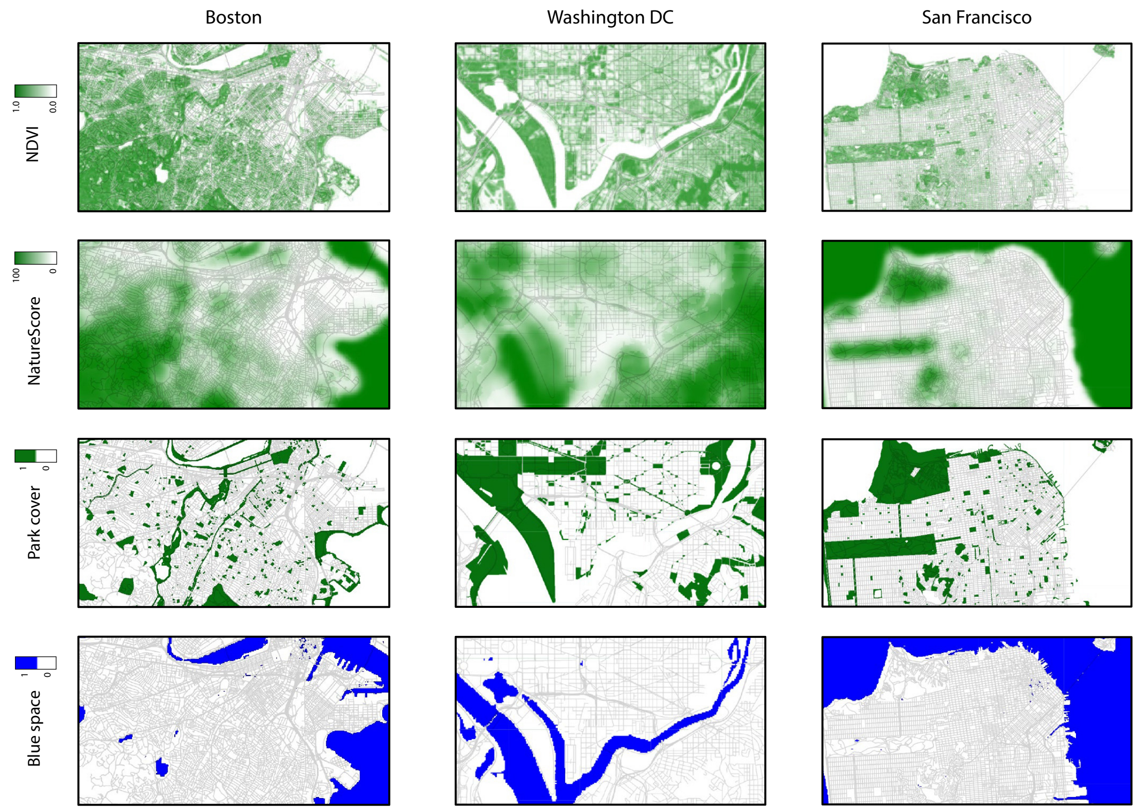

Figure 1. The spatial variation of NDVI (2020 data), NatureScore (2019 data), park cover (2020 data), and blue space (1984–2018 data) in the metropolitan areas of Boston, Massachusetts, Washington, DC, and San Francisco, California. NDVI is based on Landsat 8 images, NatureScore is a proprietary measure created by NatureQuant, Park cover was based on the USGS Protected Areas Database of the U.S. (PAD-US), and blue space was based on the European Commision's Joint Research Centre's Global Surface Water data set. Note: NDVI, Normalized Difference Vegetation Index; USGS, U.S. Geological Survey.

mean blue space within tracts and a 100-m buffer around each tract.

Potential Confounders

We downloaded data about median age and population size for each tract based on 5-y ACS estimates (2015–2019) via https://www.nhgis.org.[16] We calculated population density by dividing population size by tract land area. We defined urban tracts as tracts with $\geq 1{,}000\ \text{persons/mi}^2$.[27] For each tract, we estimated the annual average maximum temperature and daily total precipitation for the year 2020 using data from the Gridded Surface Meteorological data set at an $\sim 4\text{-km}^2$ spatial resolution.[28]

Statistical Analysis

We calculated the Spearman correlation between all four natural environment measures, SES, and race/ethnicity indicators. We used linear generalized additive models (GAMs) to evaluate associations between SES indicators and race/ethnicity with NDVI, NatureScore, and park cover. After checking modeling assumptions, we decided to use quintiles of SES indicators and race/ethnicity measures. Given that >40% of all tracts (and >60% of urban tracts) contained no blue space, we used a binary indicator for this measure ($0 = \text{absent}$, $1 = \text{present}$), and modeled associations with logistic GAMs. In all models, SES and race/ethnicity indicators were the independent variables and natural environment measures were the dependent variables. We analyzed associations in all tracts and in urban tracts ($\geq 1{,}000\ \text{persons/mi}^2$) For the analyses in urban tracts, we recalculated SES and race/ethnicity quintiles.

To evaluate potential confounding, we specified models with increasing levels of adjustment. Model 1 included the independent variable(s) %<high school education; median household income; % below poverty; %non-Hispanic White + %non-Hispanic Black + %non-Hispanic Asian + %non-Hispanic other + %Hispanic, as well as median age and splines (a full tensor product smooth)[29] for the combination of latitude and longitude of the centroid of the tract to account for spatial autocorrelation between tracts. We additionally adjusted for population density in model 2. In model 3, we additionally adjusted for annual average temperature and precipitation to account for climatic factors. For models including an SES indicator, we added all race/ethnicity measures to model 4. For models including race/ethnicity, we added median household income to model 4. We did not include all SES measures simultaneously in any single model because they were strongly correlated with each other (Spearman rho ≥ 0.65).

For sensitivity analyses, we included a random effect by state to model 4 to account for differences between states. Further, we performed analyses by U.S. Census divisions, to evaluate whether associations of median household income, % non-Hispanic Black and %Hispanic differed between geographic areas. We maintained the quintiles used in the main analyses for all stratified analyses.

To compare effect estimates for NDVI, NatureScore, and park cover, we standardized these outcomes so that beta coefficients presented a percentage increase or decrease of the standard deviation (SD) of these indicators (based on all tracts). Given that the correlation between summer and annual mean NDVI was very strong (Pearson $r = 0.96$), we only used summer NDVI (referred to as NDVI) in our analyses. Analyses were performed in RStudio

Table 1. Descriptive statistics of all census tracts ($n = 71{,}532$) and urban census tracts ($n = 45{,}338$) in the contiguous United States after excluding census tracts with missing data.

Variable	All census tracts Mean ± SD or *n* (%)	Urban census tracts Mean ± SD or *n* (%)
Land area (km^2)	108.7 ± 557.6	3.6 ± 4.0
Natural environment measures		
NDVI	0.48 ± 0.18	0.41 ± 0.15
NatureScore	64.4 ± 33.4	48.9 ± 31.5
Park cover (proportion)	0.08 ± 0.13	0.07 ± 0.10
Blue space +100 m (continuous, proportion)	0.03 ± 0.09	0.02 ± 0.08
Contains blue space +100 m	41,632 (58.2)	17,304 (38.2)
Race/ethnicity		
% non-Hispanic White	61.5 ± 29.9	51.7 ± 29.6
% non-Hispanic Black	13.5 ± 21.5	16.8 ± 23.9
% non-Hispanic Asian	4.8 ± 8.9	6.7 ± 10.3
% non-Hispanic other	3.4 ± 5.2	3.4 ± 3.0
% Hispanic	16.7 ± 21.5	21.4 ± 23.5
SES indicators		
%<high school education	12.7 ± 10.3	13.2 ± 11.3
% below the U.S. poverty level	14.1 ± 10.7	14.9 ± 11.7
Median household income (USD)	66,976 ± 33,471	68,495 ± 35,892
Potential confounders		
Population density (persons/miles^2)	5,277 ± 11,669	8,175 ± 13,852
Median age (y)	39.6 ± 7.8	37.8 ± 7.5
Annual average daily maximum temperature (°C)	20.4 ± 4.8	20.9 ± 4.8
Annual average daily total precipitation (mm)	2.9 ± 1.5	2.8 ± 1.6

Note: %, percentage; NDVI, Normalized Difference Vegetation Index; SD, standard deviation; SES, socioeconomic status; USD, U.S. dollars.

(version 1.4.1717; RStudio) and used the following packages (sp, raster, dplyr, sf, ggplot2, grid, data.table, and mgcv).

Results

Descriptive Statistics

We excluded 1.4% of all tracts in the contiguous United States because of missing data, resulting in 71,532 included tracts. Approximately 63% of the tracts were urban ($\geq 1{,}000$ persons/mi^2). NDVI levels were generally higher in the eastern United States, whereas park cover was higher in the western United States (Figure S2). Mean NDVI and NatureScore and percentage of tracts that contain blue space were substantially lower in urban tracts than across all tracts, mean park cover was weakly lower in urban tracts (Table 1, Table S1). Means ± SDs of median household income, %<poverty level, %<high school education, %non-Hispanic Black, and %Hispanic were higher in urban tracts than across all tracts.

The correlation between NDVI and NatureScore was very strong across all tracts (Spearman rho = 0.87; Figure S3), whereas correlations between other natural environment measures were weak to moderate (Spearman rho ≤ 0.40). NDVI and park cover were not correlated (Spearman rho = 0.00) across all tracts and weakly positively correlated across urban tracts (Spearman rho = 0.11). Natural environment measures were generally negatively correlated with %<poverty level, %<high school education, and %Hispanic, but positively correlated with median household income and %non-Hispanic White across all and urban tracts. We observed a clear trend between both NDVI and NatureScore and %non-Hispanic White and %Hispanic; the higher the NDVI or NatureScore, the higher the %non-Hispanic White and the lower the %Hispanic (Figure 2, Tables S2–S9).

Relations of SES and Race/Ethnicity with Natural Environment Measures

Urban tracts with higher median household incomes, lower %<poverty level, and lower %<high school education had higher levels of NDVI, NatureScore, park cover, and odds of containing blue space (Figure 3, Table S10). Urban tracts in the highest median household income quintile had higher NDVI [44.8% of the SD; 95% confidence interval (CI): 42.8, 46.8], corresponding to a 0.08 higher NDVI; NatureScore [54.9% of the SD (95% CI: 52.6, 57.3)], corresponding to a 18.3 higher NatureScore; and park cover [16.2% of the SD (95% CI: 13.5, 19.0)], corresponding to a 2.1% higher park cover, compared with urban tracts in the lowest median household income quintile. Associations with SES indicators were generally strongest for NatureScore and weakest for park cover. Across all tracts, lower median household income and higher %<poverty level were associated with lower NDVI and NatureScore; we found nonlinear associations for park cover and blue space. Associations of SES indicators with NDVI and NatureScore were generally stronger in urban tracts than across all tracts.

Urban tracts with lower %non-Hispanic White had lower NDVI and NatureScore but not park cover (Figure 4, Table S11). For %non-Hispanic Black, we observed weak positive associations with NDVI, NatureScore, and park cover in urban tracts. For %Hispanic, we did not find any clear associations with NDVI, NatureScore, and park cover. Across all tracts, higher % Hispanic and lower %non-Hispanic White had lower NDVI and NatureScore but not lower park cover. We did not observe any clear patterns between %non-Hispanic Black and NDVI, NatureScore, and park cover. Higher %non-Hispanic White and %Hispanic and lower %non-Hispanic Black were generally associated with higher odds of the tracts containing blue space.

Across all tracts and in urban tracts, associations of SES and % non-Hispanic White with NDVI, NatureScore, and blue space were generally strongest in minimally adjusted models (model 1) and mildly attenuated after adjustments for potential confounders (Figures S4–S7, Tables S12–S17). Associations of SES and %non-Hispanic White with park cover barely changed with increasing levels of adjustment. Associations of %non-Hispanic Black with NDVI, NatureScore, and park cover in urban tracts became slightly stronger after adjustment for potential confounders, especially median household income. %Hispanic was associated with lower NDVI and NatureScore in urban tracts in minimally adjusted models, but we did not notice any pattern after adjustment for potential confounders. %non-Hispanic Asian was negatively associated with NDVI and NatureScore, but positively associated with blue space (only in urban census tracts) and park cover (Table S18). Sensitivity analyses including a random effect by state showed similar results as the fully adjusted models (Tables S19–S20).

In urban tracts, positive associations of median household income with NDVI and NatureScore were generally consistent across U.S. Census divisions, whereas associations with park cover showed no clear pattern in any U.S. Census division (Table S21). Median household income was generally negatively associated with the odds of containing blue space in the Northeastern (New England, Middle Atlantic) and Western (Mountain, Pacific) divisions and positively associated with the odds of containing blue space in the Midwestern (East North Central, West North Central) and Southern (South Atlantic, East South Central, West South Central) divisions. For most divisions, associations of % non-Hispanic Black and %Hispanic with NDVI, NatureScore, park cover, and blue space in urban tracts were not consistent (Tables S22–S23); for some divisions we observed positive associations and for others we observed negative associations. For example, we observed positive associations of %non-Hispanic

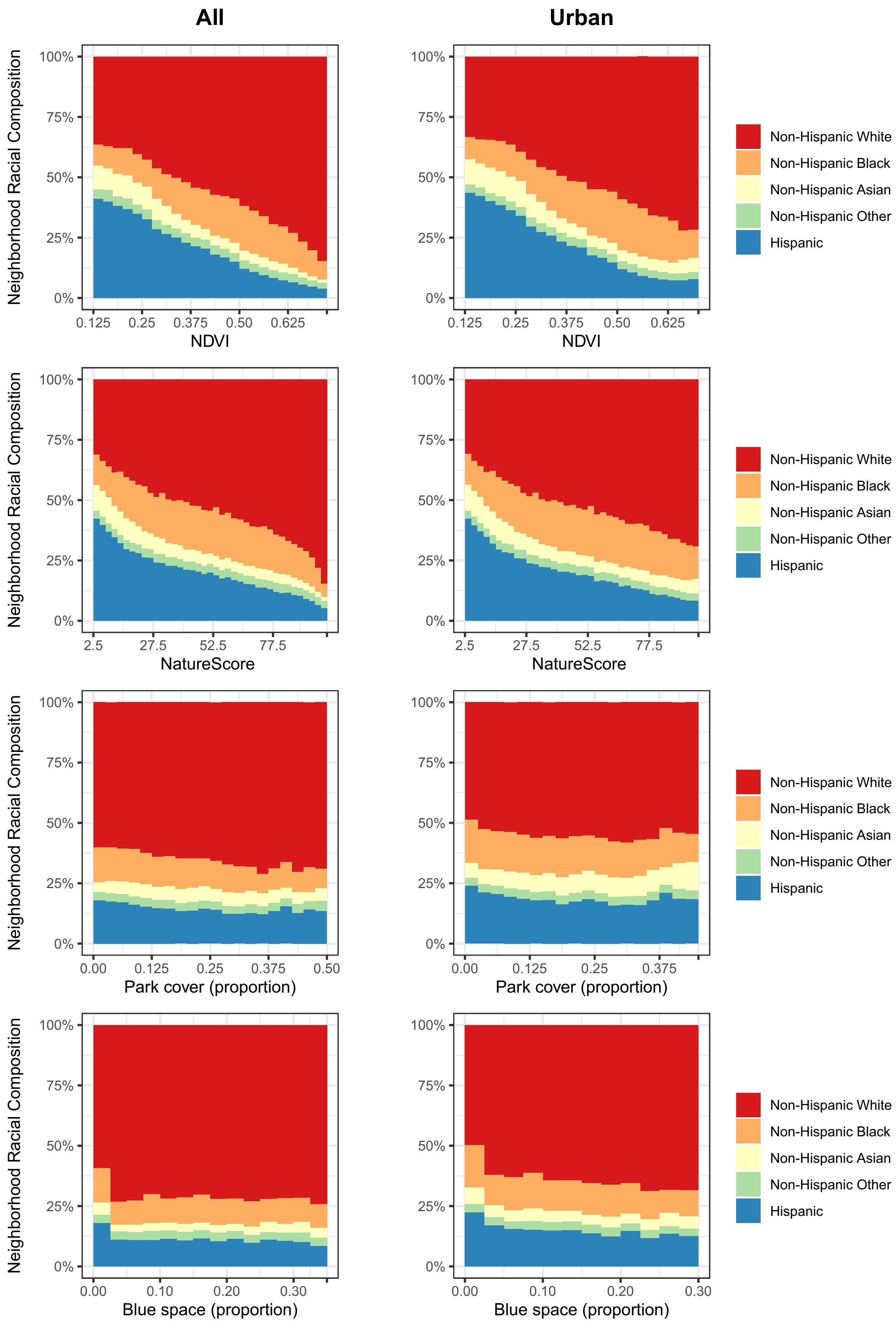

Figure 2. Average 2015–2019 race/ethnicity composition by levels of NDVI (2019 data), NatureScore (2020 data), park cover (2020 data), and blue space (1984–2018 data) in all census tracts ($n = 71,532$) and in urban census tracts ($n = 45,338$) in the contiguous United States after excluding census tracts with missing data. See Tables S2–S9 for corresponding numeric data. The x-axis of each plot was truncated by the 2.5 and 97.5 percentile. Note: NDVI, Normalized Difference Vegetation Index.

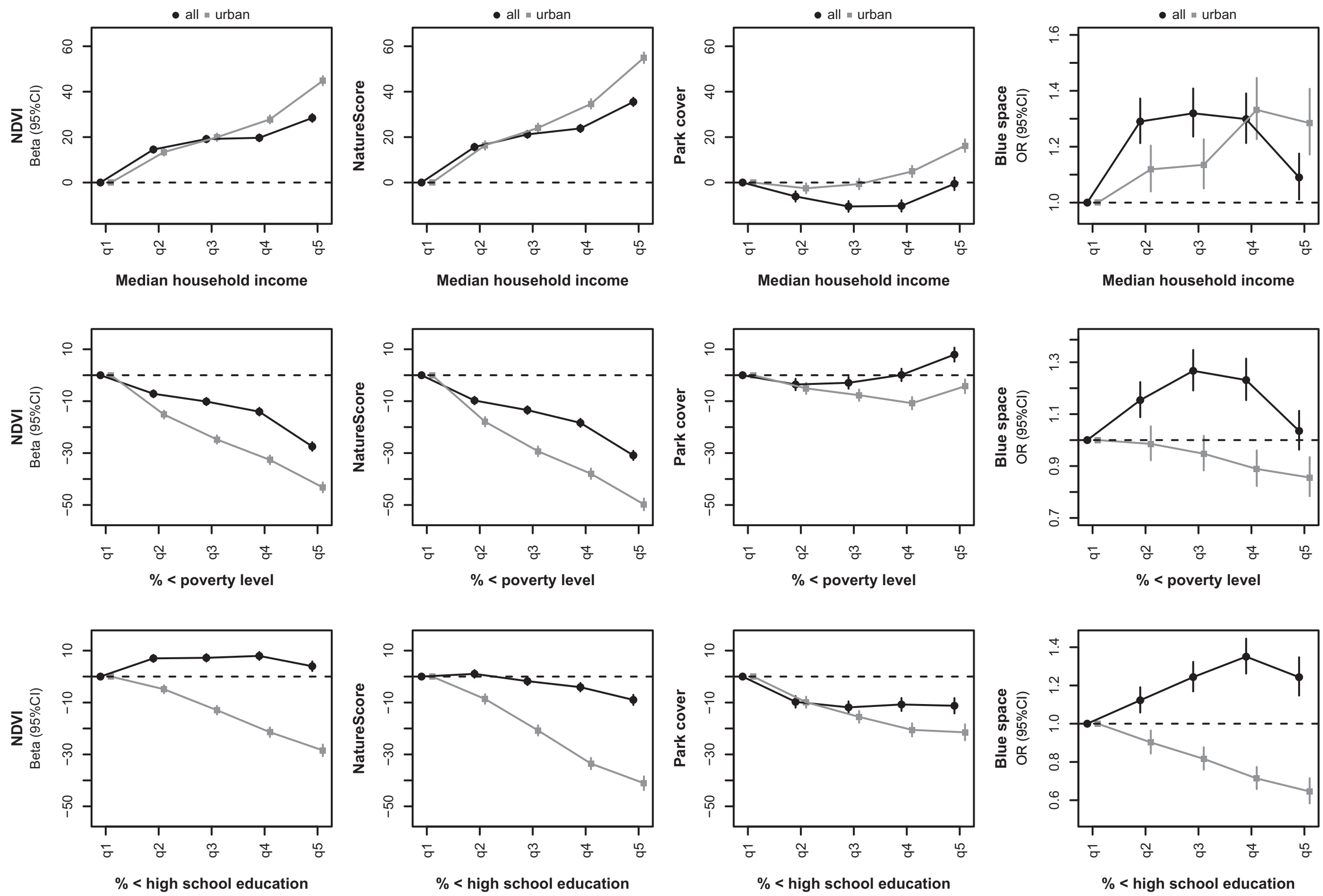

Figure 3. Associations of 2015–2019 median household income, %<poverty level, and %<high school education with NDVI (2020 data), NatureScore (2019 data), park cover (2020 data), and blue space (1984–2018 data) in all census tracts ($n = 71{,}532$, ●) and in urban census tracts ($n = 45{,}338$, ■) in the contiguous United States after excluding census tracts with missing data. See Table S10 for corresponding numeric data. NDVI, NatureScore, and park cover were standardized and multiplied by 100, so that the beta represents the percentage increase/decrease of the SD (NDVI: 0.18, NatureScore: 33.4, Park cover: 0.13). The error bars correspond to 95% CIs. Models included median household income / %<poverty level/%<high school education and were adjusted for median age, population density, temperature, precipitation, %non-Hispanic White, %non-Hispanic Black, %non-Hispanic Asian, %non-Hispanic other, %Hispanic, and latitude and longitude of the centroid. For all census tracts, the following percentiles (20, 40, 60, 80) were used to create median household income (in U.S. dollars) quintiles: 41,135, 53,214, 66,468, 88,640; %<poverty level quintiles: 5.5, 9.1, 13.7, 21.3; %<high school education quintiles: 4.4, 7.8, 12.1, 19.5. For urban census tracts, the following percentiles (20, 40, 60, 80) were used to create median household income (in U.S. dollars) quintiles: 39,435, 53,283, 69,168, 93,216; %<poverty level quintiles: 5.4, 9.2, 14.5, 23.4; %<high school education quintiles: 4.0, 7.5, 12.4, 21.2. Note: %, percentage; CI, confidence interval; NDVI, Normalized Difference Vegetation Index; OR, odds ratio; q, quartile; SD, standard deviation.

Black with NDVI and NatureScore in the Middle and South Atlantic divisions, but we found negative associations in the East South Central division.

Discussion

In urban areas across the contiguous United States, census tracts with lower SES had less greenness (i.e., NDVI), park cover, and presence of blue space and lower NatureScores. Urban tracts with lower percentages of non-Hispanic White individuals had less greenness and lower NatureScores but not less park cover; we did not find any clear patterns for percentages of Hispanic individuals. Urban tracts with higher percentages of non-Hispanic Black individuals had more NDVI, NatureScore, and park cover. Across all tracts in the contiguous United States, associations between SES and natural environment measures were mixed and differed by the specific natural environment measure. Associations with race/ethnicity were more definitive across all tracts; tracts with larger proportions of Hispanic individuals and smaller proportions of non-Hispanic White individuals had less greenness and lower NatureScores but not less park cover. The inequitable distribution of natural environments could partially explain the health disparities between SES and race/ethnicity groups in the United States given that multiple reviews have documented protective associations of natural environment with adverse health outcomes.[6–10]

Associations of SES with natural environment measures in this study are generally consistent with recent studies.[5,11,12,30,31] These associations may be due to the fact that green and blue spaces are highly valued, especially in urban areas, and proximity to natural environments and private greenery may increase house prices.[32–34] Another possible explanation could be that there is less green infrastructure investment in low SES and minority race areas than in other areas.[35] We note that associations of SES measures with NDVI and NatureScore in urban tracts were weakest for %<high school education. However, associations with park cover and blue space in urban tracts showed more consistent patterns for %<high school education than for the other measures. We have no clear explanation for this, but note that although education and income are strongly related to each other, education is generally considered an early life SES measure[36] and only indirectly (via employment and income) does it affect material resources, such as housing.

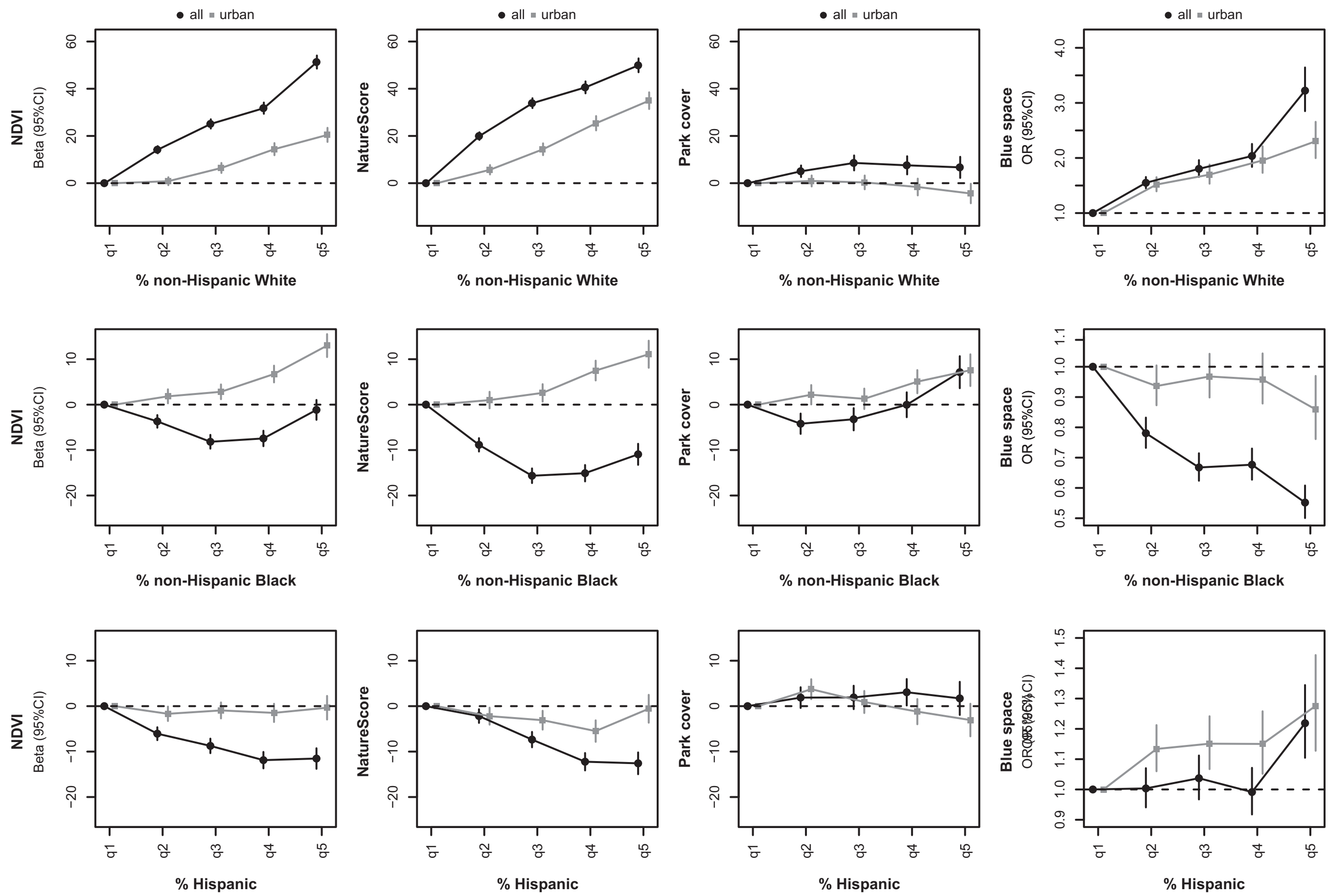

Figure 4. Associations of 2015–2019% non-Hispanic White, %non-Hispanic Black, and %Hispanic with NDVI (2020 data), NatureScore (2019 data), park cover (2020 data), and blue space (1984–2018 data) in all census tracts ($n=71{,}532$, ●) and in urban census tracts ($n=45{,}338$, ■) in the contiguous United States after excluding census tracts with missing data. See Table S11 for corresponding numeric data. NDVI, NatureScore, and park cover were standardized and multiplied by 100, so that the beta represents the percentage increase/decrease of the SD (NDVI: 0.18, NatureScore: 33.4, Park cover: 0.13). The error bars correspond to 95% CIs. Models included %non-Hispanic White, %non-Hispanic Black, %non-Hispanic Asian, %non-Hispanic Other, %Hispanic and were adjusted for median age, population density, temperature, precipitation, median household income, and latitude and longitude of the centroid. For all census tracts, the following percentiles (20, 40, 60, 80) were used to create %non-Hispanic White quintiles: 30.2, 60.4, 78.0, 89.9; %non-Hispanic Black quintiles: 0.6, 2.4, 6.8, 20.3; %Hispanic quintiles: 2.1, 5.2, 11.1, 27.0. For urban census tracts, the following percentiles (20, 40, 60, 80) were used to create %non-Hispanic White: 18.0, 45.8, 66.3, 81.1; %non-Hispanic Black quintiles: 1.3, 4.0, 9.7, 26.0; %Hispanic quintiles: 3.7, 8.3, 16.6, 36.6. Note: %, percentage; CI, confidence interval; NDVI, Normalized Difference Vegetation Index; OR, odds ratio; q, quartile; SD, standard deviation.

In general, we observed that SES was more strongly associated with NDVI compared with park cover, which supports findings by Nesbitt et al.[15] This is probably because NDVI captures street and private greenery, which may contain a large portion of the total greenness in urban areas, and high SES neighborhoods generally have larger residential properties. We also observed a very weak correlation between NDVI and park cover in urban tracts (Spearman rho $=0.11$). Not all parks contain dense vegetation, especially in dry areas of the western United States. Further, urban parks could include paved paths, playgrounds, and basketball courts that are not captured by NDVI. Moreover, there might be fewer parks in (suburban) areas with large backyards and tree-lined streets. We also note that NDVI was very strongly correlated with NatureScore and that associations with both measures and SES and race/ethnicity were similar. NatureScore is a blend of several natural elements, including park space, noise, air pollution, and satellite infrared vegetation measurements, and proximity to greenness is one of the most heavily weighted elements in the NatureScore. Further, associations of SES measures with blue space showed non-linear patterns across all tracts. This could be due to harbors and air pollution sources (e.g., ships) in/close to blue spaces that may not be highly valued or provide beneficial health effects.

We found weak positive associations between %non-Hispanic Black and NDVI, NatureScore, and park cover in urban tracts. Associations became more pronounced after adjustment for median household income. This is likely due to the moderate negative correlation (Spearman rho $= -0.41$) between %non-Hispanic Black and median household income. A review by Watkins and Gerrish reported no urban forest inequity for Black populations.[13] Casey et al. reported a positive association of %non-Hispanic White and a weak negative association of %non-Hispanic Black with a change in NDVI 2001–2011 in urban census tracts.[37] A review by Rigolon reported that White individuals had more urban park acreage than Black or Hispanic individuals,[11] whereas we observed no clear associations of %non-Hispanic White or %Hispanic with park cover in urban tracts. Differences in associations between these studies might be due to differences in adjustment for potential confounders and spatial autocorrelation, exposure assessment, and study years. Moreover, we observed that associations of race/ethnicity with natural environments differed between U.S. Census divisions, indicating that associations could differ between study regions.

Associations of %non-Hispanic White with NDVI and NatureScore were generally weaker in urban tracts than across all tracts, in contrast to patterns with SES indicators. For %non-

Hispanic Black and Hispanics, we observed negative associations with NDVI and NatureScore in all tracts, but not in urban tracts. This may partially be due to urban–rural patterns that emerge in models with all the tracts. In densely populated areas, NDVI, NatureScore, and percentage of tracts containing blue space were lower than in more rural areas. Given that population density is more strongly correlated with %non-Hispanic White, %non-Hispanic Black, and %Hispanic across all tracts compared with urban tracts, this may have resulted in stronger associations with race/ethnicity in models that included all tracts than in models with only urban tracts, despite adjustments for population density. Because SES measures were weakly correlated with population density, this pattern may not have affected associations of SES indicators. Further, we note that associations of %non-Hispanic Black and %Hispanic with NDVI and NatureScore differed between divisions, whereas associations of median household income were generally consistent across all divisions.

We observed no clear pattern between %Hispanic and NDVI, NatureScore, and park cover in urban tracts. A weak negative association of %Hispanic with change in NDVI 2001–2011 was observed by Casey et al.[37] Choi et al. observed negative associations between %Latino with street greenery, but they observed positive associations with green space accessibility in 12 U.S. cities.[38] The review by Watkins and Gerrish also reported urban forest inequities for Hispanic populations.[13] However, when studies that did not control for income were removed, no inequities were found.[13] We observed a similar trend; patterns of associations with NDVI, NatureScore, or park cover disappeared after adjustment for income. In all tracts, we observed that a higher % Hispanics was associated with lower NDVI and NatureScore. We note that the percentage of Hispanic residents was highest in the southwest United States, which is a region with generally low NDVI (Figures S1 and S2). Hence, the negative associations with NDVI and NatureScore might be due to the large-scale spatial variation of these variables.

Our results are comparable to two studies that showed redlined neighborhoods (i.e., those ineligible for federal mortgage programs in the 1930s) had less green space in urban areas.[39,40] Today, redlined neighborhoods are still generally composed of lower SES, Black, and Hispanic populations.[41] Both studies that focused on redlined neighborhoods used green space measures that included private greenery,[39,40]; they did not evaluate associations with park cover or blue space.

Limitations

This study has a few limitations. We used cross-sectional data, so we did not evaluate how associations of SES or race/ethnicity with natural environment change over time. NDVI and NatureScore do not differentiate between private and public greenery; hence, we do not know whether vegetation on private or public land is primarily responsible for the observed inequities. We acknowledge that the park data set is based on "best available" data provided by land management agencies and organizations; therefore, it may not be completely accurate or comprehensive. We used satellite imagery from 1984–2018 at a 30-m^2 spatial resolution with a 50% threshold to classify blue spaces and may have missed some water bodies that are more ephemeral. Although blue space data was aggregated over multiple years in this data set, we do not think that this would affect our results because the spatial distribution of most water bodies is relatively stable over time.[42] We used a binary blue space indicator because of the limited variability and did not evaluate whether tracts with low SES or high %non-Hispanic Black or % Hispanic had lower blue space levels. Given that blue space is based on satellite images, we did not differentiate between types of blue spaces (e.g., oceans, lakes, rivers). We used four diverse natural environment metrics, but we note that other studies used metrics based on land use/cover databases.[6,7] Recently, studies have also classified greenness based on street view images.[43,44] Associations with these metrics may differ from associations with the metrics used in this study. We also used census tracts as our unit of observation, but residents may travel across tract boundaries to access nature. Further, we note that this is an ecological study and that ecological studies should not be used to make inferences about individuals.

Strengths

This study also has several strengths. To the best of our knowledge, this is the first study to cover all census tracts in the contiguous United States and to use diverse natural environments metrics to assess whether natural environments vary by SES and race/ethnicity. We evaluated associations across all tracts and in urban census tracts. We adjusted for several potential confounders and corrected for spatial autocorrelation. In addition, we used four metrics of natural environments that capture different aspects of nature that might have independent influences on health. SES and race/ethnicity measures were based on 2015–2019 estimates, NatureScore was based on data from 2019, and NDVI and park cover were based on data from 2020.

Conclusion

In short, we observed an inequitable distribution of natural environments by SES and race/ethnicity in the contiguous United States. The strength of the associations differed between the natural environment measures used. Associations with SES were stronger in urban tracts than across all census tracts, whereas associations with %non-Hispanic White were stronger across all census tracts than in urban tracts. Assuming that exposure to natural environments is protective against several adverse health outcomes, the inequitable distribution of natural environments may partly explain health disparities observed in the United States. Increasing green and blue spaces in urban areas can be challenging and may result in green gentrification.[45] Therefore, urban planners should target green and blue space interventions in an equitable way that could promote healthier environments in marginalized communities.[46]

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