Title: Who has nature during the pandemic? COVID-19 cases track widespread inequity in nature access across the United States

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Abstract

Urban nature can alleviate distress and provide space for safe recreation during the COVID-19 pandemic. However, nature is often less available in low-income and communities of color—the same communities hardest hit by COVID-19. We quantified nature inequality across all urbanized areas in the US and linked nature access to COVID-19 case rates for ZIP Codes in 17 states. Areas with majority persons of color had both higher case rates and less greenness. Furthermore, when controlling for socio-demographic variables, an increase of 0.1 in Normalized Difference Vegetation Index (NDVI) was associated with a 4.1% decrease in COVID-19 incidence rates (95% confidence interval: 0.9-6.8%). Across the US, block groups with lower-income and majority persons of color are less green and have fewer parks. Thus, communities most impacted by COVID-19 also have the least nature nearby. Given urban nature is associated with both human health and biodiversity, these results have far-reaching implications both during and beyond the pandemic.

Introduction

The COVID-19 pandemic has exposed many existing inequalities in the US. The unprecedented impacts of the COVID-19 pandemic, including upsets to daily life, economic loss, and emotional distress, have fallen disproportionately on low-income populations and communities of color[1–4]. These same groups have also faced greater exposure to COVID-19 through high public-contact jobs[5] that often make social distancing difficult or impossible, and higher rates of cases as a result[2,3,6–9].

Access to nature is also unequally distributed in the US, with vegetation and parks often less available in low-income neighborhoods and communities of color. Many studies[10–15] have shown persistent patterns of inequality in individual cities, groups of cities, and nationwide for Normalized Difference Vegetation Index (NDVI) at the census-tract scale[16]. Thus, the communities most impacted by COVID-19 may have the least access to nature. A negative association between COVID-19 case rate and greenness has been shown with county-level data in the United States[17], but it is not known whether this effect holds when using finer spatial resolution data, nor whether park access has the same negative association with COVID-19 case rate.

Nature has the potential to reduce some of the distress associated with the pandemic by improving mental health and providing safe spaces for socializing, physical activity, and recreation[18–20]. Access to greenness (defined here as the total volume of vegetation in an area, quantified using NDVI) and parks has been tied to physical and mental health, including lower risk of mortality, lower odds of depression, and lower rates of obesity and chronic diseases such as diabetes and cardiovascular disease[21–23]. Thus, inequalities in nature access have the potential to translate into inequities in mental and physical health both during and beyond the pandemic.

In this study we document the extent of these two, "stacked" inequalities; that is, that low income and majority people of color (POC) communities have both more COVID-19 cases and less nature. We also explore whether there is an association between access to nature and COVID-19 incidence after accounting for income, race/ethnicity, and other potentially confounding variables. There are multiple mechanisms that could produce such an association. For instance, a lack of access to nature might not only deprive individuals of a much-needed mental health resource but may also actively interfere with the body's ability to fight infection. Contact with nature appears to play an important role in our defenses against viruses though boosting Natural Killer (NK) cells[24,25]. This and other mechanisms could keep a higher proportion of cases subclinical or asymptomatic in areas with more nature. This would result in a negative correlation between greenness and COVID-19 case rates that persists after accounting for socio-demographic characteristics and other factors that are also likely to be related to both greenness and COVID-19. While other mechanisms could also produce this pattern, a first step is to identify whether such a correlation exists.

Here, we quantify nature inequality across all census block groups in urbanized areas in the US and link inequality in nature access to rates of COVID-19 cases for ZIP Codes in 17 states. Specifically, we ask: 1) Do low-income and predominantly POC communities have both higher COVID-19 case rates and less nature access (defined here by NDVI and park proximity), 2) Is nature access related to COVID-19 case rates after accounting for income, race/ethnicity, and other potentially confounding variables, and 3) Do inequalities in nature access persist when examined at resolutions finer than the census tract? We quantify nature access for both parks and greenness in order to ask whether inequality is systematic across all urbanized areas in the US.

Results

We found that majority POC ZIP Codes had both higher COVID-19 case rates and less greenness (Fig. 1). As of September 30, 2020, majority POC ZIP Codes had nearly twice as many COVID-19 cases per 100,000 people compared to white majority ZIP Codes (Fig. 1). Less green ZIP Codes also had higher rates of COVID-19 cases even after controlling for differences in population density, race/ethnicity, income, time since the first recorded case, age, and state (Fig. 2). In a negative binomial mixed effect model of COVID-19 cases, we found a 4.1% decrease in COVID-19 cases with a 0.1 increase in NDVI (Incidence Rate Ratio 95% CI: 0.9 - 6.8%). Unlike NDVI, park proximity was not significantly related to COVID-19 case rates when controlling for other variables (Fig. 2). We also found that when controlling for race/ethnicity, NDVI, and age, other factors including income, population density, and the number of days since the first recorded case were not significantly related to the number of cases. While the virus arrived later in lower-density areas, it also tended to hit a larger fraction of the population (Extended Data Table 1), which could explain why both population density and the time since the first recorded case were poor predictors of COVID-19 case rates during the study period.

We also found inequality in nature access at the US scale. Across all urbanized areas, block groups with a majority POC are less green (0.1 lower NDVI on average) and have fewer parks (0.5 fewer hectares on average). Similarly, low-income block groups are also less green (0.09 lower NDVI on average) and have fewer parks (3.6 fewer ha on average, Fig. 3, Extended Data Table 2). For context, a 0.1 magnitude difference in NDVI is roughly equivalent to a one standard deviation (SD) difference in greenness in our sample: the SD in NDVI across all block groups is 0.15, and the average within-city SD is 0.08. In simultaneous autoregressive models (SAR) that account for spatial autocorrelation, the proportion white people in a block group and median household income were both significant predictors of NDVI and park proximity (Extended Data Fig. 1). Similarly, statistically significant differences in access to nature remain after accounting for population density (in both models of park proximity and greenness) and aridity (in the model of greenness).

Discussion

Taken together, our results demonstrate that COVID-19 has inflicted the greatest burden on communities that also face widespread inequity in nature access. These results have potentially important implications for how communities and individuals manage mental health and social interactions during a pandemic where socializing, recreation, and physical activity with others are most safely conducted in outdoor spaces.

We found an association between greenness and COVID-19 case rates after accounting for income, race/ethnicity, and other confounding factors. While observational data such as ours cannot speak to causal relationships, previous findings from the literature suggest possible mechanisms that could explain this statistical association. Greenness might affect COVID-19 case rates if it helps the body fight the virus once exposed, keeping a higher proportion of cases subclinical or asymptomatic. Natural Killer (NK) cells play a key role in the body's defense against viral infections, seeking out and attacking or "clearing" virus-infected cells[24,25]. Contact with nature appears to play an important role in boosting our NK defenses: two two-hour forest walks on consecutive days increase the number and activity of anti-cancer NK cells by 50 and 56%, respectively, and activity remained significantly boosted even a month after returning to urban life—23% higher than before the walks; by contrast, urban walks had no such effect[26]. Another possible explanation for the nature-COVID-19 association is that having less green in a neighborhood makes it more difficult to safely socialize in outdoor spaces. While either, both, or none of these explanations might underlie the lower rates of COVID-19 in areas with greater access to nature, this finding raises the possibility that populations that lack ready access to nature during the pandemic may not only be deprived of a much needed mental health resource but may also be at greater risk of contracting COVID-19. Further research using patient-level data is needed to uncover the mechanistic drivers behind the patterns we show in this work.

We found widespread evidence of inequality in access to nature across urbanized areas in the US. These results may have cascading impacts, given nature in urban settings has been associated with many human health benefits while also supporting other ecosystem services and biodiversity[21,22,27–29]. These patterns are consistent with other studies that have shown inequality in access to parks and greenness[10,13,15,16,30,31], and here, we show nature inequality patterns at a finer resolution than has been shown previously in the US. Placing our results in context, a difference of 0.1 increments of NDVI has been linked in other research to specific health impacts. For example, living with 0.1 increments lower NDVI around the home has been linked to 12% higher all-cause mortality[32], 20.6 g lower birth weight in infants and higher likelihood of preterm birth[33], 10% higher odds of poor self-reported health, lower neighborhood satisfaction and social capital[34], and a 39% decrease in odds of moderately vigorous physical activity in children[35]. Similarly, the area of available greenspace has also been linked to health; pregnant women living in neighborhoods without a greenspace larger than 0.5 ha within 300 m are 13% more likely to report depressive symptoms[36], and living closer to larger parks or more total area of parks has been associated with less stress[37], more physical activity[38], and lower odds cardio-metabolic disease[39]. These results suggest that differences in access to greenness and parks of a similar magnitude as shown here have the potential to impact a range of physical and mental health outcomes for low-income populations and communities of color.

We show that the pandemic has compounded the disadvantages in low-income areas and communities of color already facing fewer acres of park available for recreation and less greenness. Our results suggest that inequity in nature access has potential public health implications during a period of profound social and economic upheaval and mental health distress. In the short term, actions to overcome barriers to nature access during the pandemic, such as keeping urban parks in low-income neighborhoods and communities of color open, safe, and accessible could help to relieve some of the distress associated with the pandemic. Over the longer term, actions taken to redress inequity through park creation and greening interventions could have substantial broader public health value beyond the pandemic.

Methods

We combined spatially explicit data on nature access, socio-demographic characteristics, and COVID-19 case rates. We conducted two separate analyses at separate spatial scales, both limited to urban areas. In the first, we combined COVID-19 data with nature access and socio-demographic data at the ZIP Code scale across 17 states to ask whether communities with the highest COVID-19 case rates also have less access to nature. In the second analysis, we related nature access with socio-demographic data across all 486 Urbanized Areas in the US at the block group scale to explore US-wide patterns of nature inequality.

Data. *Study extent*. For the COVID-19 analysis, the availability of fine-scale case data limited the study sites to 17 states that provide publicly accessible state-wide data at the ZIP Code scale. While individual counties also publish COVID-19 case data at the ZIP Code scale, the timelines, systems, and formats for reporting and publishing these data are variable and inconsistent, and reconciling these differences were beyond the scope of this analysis. We limited our analysis to the ZIP Code scale because the alternative county scale is large enough to contain significant heterogeneity in both greenness and socio-demographic characteristics which could obscure relationships among these variables. We limited our analyses to ZIP Codes that contain centroids (i.e., geographic center) within either Urbanized Areas (greater than 50,000 people) or Urban Clusters (greater than 20,000 people) as defined by the US Census Bureau. We also removed 66

ZIP Codes with a median age value of 0, as well as 382 Zip Codes with a median income value of 0. The remaining dataset contained 2,652 urban ZIP Codes across the 17 states in our analysis.

For the nature equity analysis, we considered US Census block groups across all 486 urbanized areas (excluding urban clusters) in the US (excluding Puerto Rico), including 142,325 block groups and 5,197 incorporated cities. Each state was represented by at least one urban area.

COVID-19 data. We compiled publicly available COVID-19 case data at the ZIP Code scale from individual state department of health websites on October 1, 2020, including data up to between September 1 and 30, 2020 for all states (Extended Data Table 1). We considered only reported cases of COVID-19 in the earlier phases of the pandemic (March through September), because some states, such as New Jersey, ceased to update their websites with new ZIP Code-scale data beyond September. We were not able to obtain locally specific data quantifying the variation in rates of testing among different demographic groups. Evidence from some states (e.g., Illinois, see Extended Data Table 1) suggests that minority groups were being tested at much lower rates than whites, particularly in the early phases of the pandemic. These data would likely have strengthened our results, since we found that POC majority ZIP Codes have both higher case rates and less greenness.

We compared COVID-19 case rates to nature access and socio-demographic variables using data described below. We calculated case rates as the cumulative number of cases per 100,000 people for each ZIP Code using the total population for each ZIP Code Tabulation Area (ZCTA) from the American Community Survey (ACS) 2018. ZCTAs were designed to represent ZIP Code routes as two dimensional areas, and while there are minor discrepancies in some places, they are not common in the urban areas included in this analysis[40]. We also calculated the total days since the first recorded case (available only at the county scale) for each ZIP Code, using data from the New York Times US Coronavirus Database[41].

Nature access data. To quantify inequality in nature access, we used to metrics to quantify nature access: the amount of greenness and proximity to parks. We calculated these two metrics at the level of US Census block groups for nature inequity analyses and ZIP Codes for COVID-19 analyses. Greenness was quantified using NDVI, which measures the reflectance of green vegetation, and is linked to the amount, health, and leaf characteristics of vegetation, with unitless values that vary from -1 to 1. Values between 0.2 and 1 vary from sparse to heavily vegetated, and values close to or below zero represent other types of land cover such as impervious cover, water, clouds, or snow. Average NDVI values were calculated across each block group (nature equity analysis) or ZIP Code Tabulation Area (ZCTA) (COVID-19 analysis). NDVI data was derived from Landsat imagery and processed using Google Earth Engine, filtering images from 1/1/2017 to 12/31/2018 to correspond most closely to the time period in which socio-economic and demographic data was collected. In order to account for broad geographic patterns in NDVI, which varies at regional scales based on climate and aridity, we included the Global Aridity Index in our model for NDVI inequity. This publicly available dataset represents the ratio between precipitation and vegetation water demand, where higher values represent more humid conditions[42].

To measure park proximity, we generated a database of publicly accessible parks in the US that is as comprehensive as possible by combining four publicly available nationwide datasets. These datasets together included 337,441 parks across the entire US, 143,228 of which are contained within the 486 urbanized areas in the US (Trust for Public Land ParkServe, US

Protected Areas Database, National Conservation Easement Database, and ESRI Parks, see Extended Data Table 4). We did not exclude parks below a size threshold, nor did we filter parks based on characteristics such as amount of greenness or recreation type. Therefore, our dataset includes small municipal parks that may have relatively little nature if their primary function is to provide sports facilities such as basketball courts, playgrounds, or other types of recreation that typically require large impervious surfaces.

Park proximity was calculated as the total acres of park within 1,000 m of the centroid of census blocks. This distance corresponds roughly to a 10 minute walk, a common metric used by parks advocates and for measuring park accessibility[43,44]. For both ZIP Codes and block groups, population-weighted averages were taken of block-level park proximity to derive a park proximity value for each ZIP Code and block group. These population-weighted estimates were calculated to reduce the effect of areas with high park proximity where very few people live.

Socio-demographic data. Socio-economic and demographic data were obtained from the US Census Bureau 2014-2018 American Community Survey 5-year estimates[45], which summarize data collected from 1/1/2014 to 12/31/2018. These data were collected for all block groups with their centroid within US urbanized areas (nature inequality analysis) and for Zip Code Tabulation Areas (ZCTA) within the 17 states that report COVID-19 data at the ZIP Code scale (COVID-19 analysis). Variables included median household income, the number of white people in a block group or ZCTA, median age, and total population (used to derive population density, and the proportion POC in the block group or ZCTA).

Statistical analyses. We conducted two analyses at different spatial scales. In the first, we analyzed COVID-19 rates using data from 17 states at the ZIP Code scale using a negative binomial generalized linear mixed effects model. In the second, we quantified nature inequality in all urbanized areas in the US at the block group scale. This analysis used SAR models to relate NDVI and park proximity to socio-demographic factors. All analyses were performed in R (version 4.02)[46]. SARs were performed using the package spdep[47], and negative binomial mixed effects models were performed using the package lme4[48].

COVID-19. We analyzed COVID-19 case rates by ZIP Code using a negative binomial generalized linear mixed effects model, after verifying the absence of significant spatial autocorrelation using the Moran's *I* statistic[49]. A single full model related COVID-19 case rates in each ZIP Code to fixed effects for NDVI, park proximity, the proportion white people, median income, population density, median age, and the total number of days since the first recorded case (county-scale). We included state as a random effect to account for the non-independence of data from the same state that could occur as a result of processes we are not capturing with available data, such as differences in the timing of public policy responses such as lockdowns or mask mandates[49]. All explanatory variables were centered and scaled. To estimate the impact of a 0.1 increment change in NDVI, We fit an additional model using unscaled NDVI multiplied by 10 (all other variables scaled) in order to calculate the Incidence Rate Ratio (IRR), or exponentiated effect estimates and their 95% confidence intervals, to determine how a 0.1 increment of change in NDVI affects COVID-19 case rates[50].

Nature inequality. To evaluate the relationship between nature access and socio-demographic variables, we built two models and analyzed park proximity and NDVI separately. Both models included median income, the proportion white people, and the population density in the block group as covariates, and the aridity index was also included in the NDVI model. We evaluated whether spatial autocorrelation was present using the regression residuals from an ordinary least squares model using the Moran's *I* statistic. At the block group scale, models for NDVI (Moran's $I = 0.64$, P Value <0.001) and park proximity (Moran's $I = 0.62$, P Value < 0.001) models both contained evidence of significant spatial autocorrelation. To address this issue, we used SAR error models, which include a spatial error term defined from a neighborhood matrix and autocorrelation in the dependent variable[51]. These models assume the autoregressive process is found only in the error term, such as when spatial autocorrelation is not fully explained by the included explanatory variables[52].

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Figures

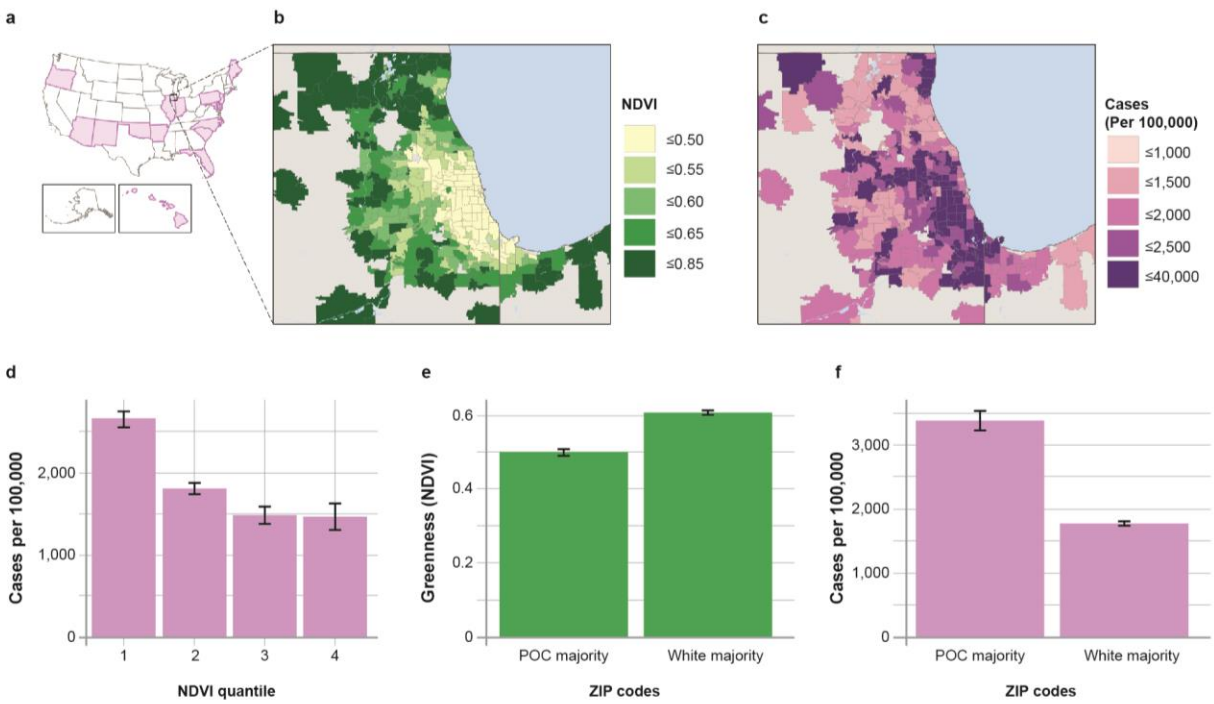

Fig. 1 | COVID-19 case rates are related to both greenness and race/ethnicity. **a**, This analysis used reported COVID-19 cases at the ZIP Code scale from 17 states. **b**, Average NDVI values and **c**, COVID-19 case rates per 100,000 people across ZIP Codes around Chicago, IL, as an example. **d**, Barchart of greenness (NDVI) represented as quantiles and rates of COVID-19 showing a decline in cases with higher NDVI. **e**, Barchart of greenness showing higher greenness in white majority ZIP Codes. **f**, COVID-19 case rates (per 100,000) showing lower rates of cases in majority white ZIP codes. Error bars represent approximate 95% confidence intervals.

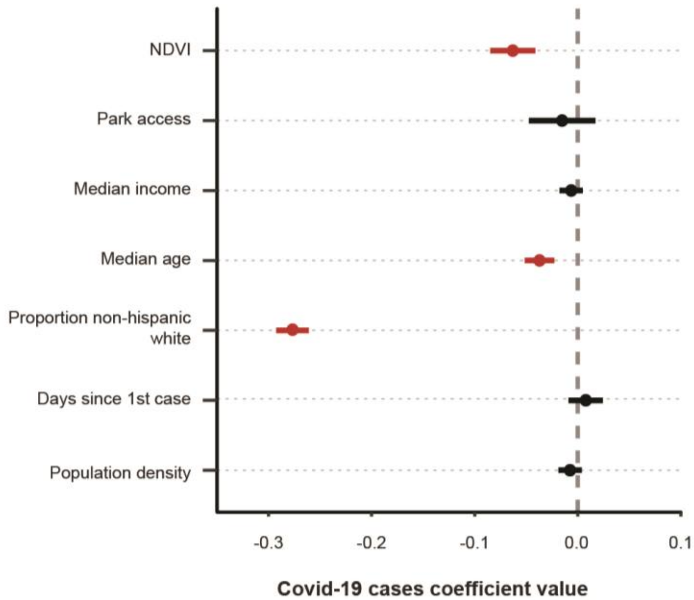

Fig. 2 | Greener ZIP Codes have fewer COVID-19 cases after accounting for other factors. Coefficient values represent effect sizes from a negative binomial mixed effects model for the relationship between rates of COVID-19 (cases/100,000 people) and greenness (NDVI), park access (ha), median income, median age, proportion persons of color, days since the first case (county-scale), and population density. Coefficient values are represented as dots, bars represent 95% confidence intervals, and significant variables are shown in red.

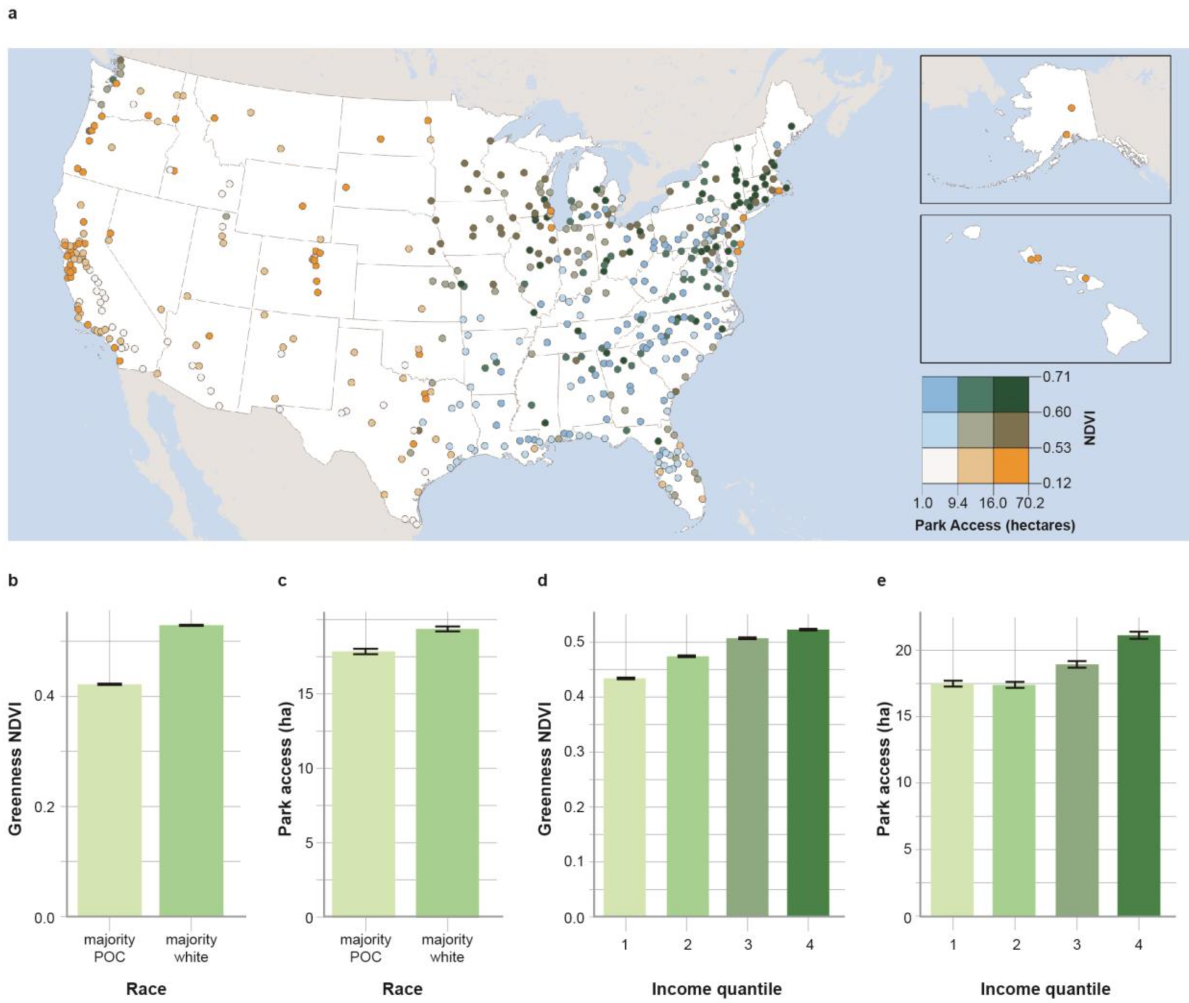

Fig. 3 | Nature access is inequitably distributed across urbanized areas in the US. **a**, Greenness (NDVI) and park proximity (hectares) across all 486 urbanized areas in the US (including 142,325 block groups). Urbanized areas are represented by a point, and values for greenness and park proximity are within-urbanized area averages. **b**, Barchart of greenness (NDVI), and **c**, park proximity by race/ethnicity, showing higher greenness in white majority block groups. **d**, Barchart of greenness (NDVI) and **e**, park proximity across all income quantiles, showing higher greenness and more parks in block groups with higher income. Error bars represent approximate 95% confidence intervals.

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