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COVID-19 infection rate but not severity is associated with availability of greenness in the United States

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HIGHLIGHTS

- The associations between availability of greenness and COVID-19 outcomes are examined.
- Availability of greenness is associated with lower rates of COVID-19 infection.
- Availability of greenness has limited effects for ameliorating COVID-19 related inequity.
- The findings provide working hypotheses for effectively designing nature-based interventions.

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ABSTRACT

Human exposure to greenness is associated with COVID-19 prevalence and severity, but most relevant research has focused on the relationships between greenness and COVID-19 infection rates. In contrast, relatively little is known about the associations between greenness and COVID-19 hospitalizations and deaths, which are important for risk assessment, resource allocation, and intervention strategies. Moreover, it is unclear whether greenness could help reduce health inequities by offering more benefits to disadvantaged populations. Here, we estimated the associations between availability of greenness (expressed as population-density-weighted normalized difference vegetation index) and COVID-19 outcomes across the urban–rural continuum gradient in the United States using generalized additive models with a negative binomial distribution. We aggregated individual COVID-19 records at the county level, which includes 3,040 counties for COVID-19 case infection rates, 1,397 counties for case hospitalization rates, and 1,305 counties for case fatality rates. Our area-level ecological study suggests that although availability of greenness shows null relationships with COVID-19 case hospitalization and fatality rates, COVID-19 infection rate is statistically significant and negatively associated with more greenness availability. When performing stratified analyses by different sociodemographic groups, availability of greenness shows stronger negative associations for men than for women, and for adults than for the elderly. This indicates that greenness might have greater health benefits for the former than the latter, and thus has limited effects for ameliorating COVID-19 related inequity. The revealed greenness-COVID-19 links across different space, time and sociodemographic groups provide working hypotheses for the targeted design of nature-based interventions and greening policies to benefit human well-being and reduce health inequity. This has important implications for the post-pandemic recovery and future public health crises.

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1. Introduction

Since the first case of the 2019 novel coronavirus (COVID-19) was reported on January 21, 2020 in the state of Washington (Wen et al., 2020), the United States (US) has witnessed a rapid explosion of COVID-19 cases. Although anyone exposed to severe acute respiratory syndrome coronavirus 2, the causative agent of COVID-19, is susceptible to infection, the burden of the COVID-19 pandemic is felt disproportionately by disadvantaged and marginalized groups (Carrión et al., 2021; Lu et al., 2021). The disparity has exacerbated the long-lasting social and health inequalities that are deeply rooted in the US society (Williams et al., 2019), which calls for interventions that could both slow down the transmission rates and reduce the overwhelming health burden being placed on socially vulnerable and economically disadvantaged groups.

Before the widespread distribution and use of vaccinations, the US and other countries relied heavily on non-pharmaceutical interventions to help slow the spread of COVID-19 (Bonaccorsi et al., 2020; Huang et al., 2022; Jin et al., 2021). Such approaches include, but are not limited to, economic lockdown for nonessential businesses, work-from-home regulations, social distancing, face coverings in public, gathering bans, out-of-state travel restrictions, and self-isolation and quarantine. Although effective for alleviating the adverse impacts of COVID-19, these strategies also come with many unintended health consequences ranging from increased levels of anxiety, depression, and mental health disorder, to the worsening of various chronic noncommunicable diseases (Labib et al., 2021). This is probably because the pandemic, economic recession, and social lockdown are conducive to the development of unhealthy lifestyles and behaviors (e.g., physical inactivity, and greater consumption of convenience foods), negative emotions (e.g., loneliness and lack of social interaction, higher levels of anxiety, insecurity, and fear), and other symptoms of mental illness.

As a nature-based solution and strategy, the health benefits of greenness have been increasingly recognized, mainly through providing ecosystem services (Bratman et al., 2019; Frumkin et al., 2017). These include air pollutant removal, heat reduction, noise mitigation, energy conservation, water purification, and protection from flooding, among many others (Bratman et al., 2019; Lin et al., 2019). In addition, greenness has the potential to increase people's physical activities (e.g., walking, bicycling, gardening, exercising, and other leisure activities) and promote their positive emotions and life satisfaction. The improved environmental quality and changes in people's behaviors and perceptions could potentially lead to better health conditions. Previous studies summarize the health effects of greenness as the following pathways: reducing harm, restoring capacities, building capacities, and causing harm (Markevych et al., 2017; Marselle et al., 2021). Specific to COVID-19, recent studies have shown that greenness is generally associated with lower COVID-19 infection (Jiang et al., 2021; Klompmaker et al., 2021) and mortality (Lee et al., 2021; Russette et al., 2021). Although positive associations between greenness and COVID-19 risk are also reported (Huang et al., 2020; Pan et al., 2021), the net benefit of greenness tends to be positive if social distancing is properly maintained (Labib et al., 2021). While these results do not prove causality between greenness and COVID-19, the revealed negative associations have important implications for reducing COVID-19 transmission and risk. In addition, greenness could ameliorate adverse health outcomes and unhealthy lifestyles associated with social lockdowns and isolation. Several studies call for an urgent need for greenspace during the pandemic (Geary et al., 2021; Kleinschroth and Kowarik, 2020).

Here we intend to advance the understanding of the greenness-COVID-19 associations by employing different indicators of COVID-19 outcomes, and a relatively long time period and large geographical scope. Although many studies examine the greenness-COVID-19 associations, these studies heavily emphasize the urban areas and the early and moderate stages of the pandemic. How the associations vary across the urban–rural gradients and different stages of the pandemic (e.g., the early, moderate, and peak periods) remain relatively unexplored. In addition, the benefit of greenness is often evaluated as decreased COVID-19 incidences or infection rates (Jiang et al., 2021; Lu et al., 2021), while the severity of diseases is often less considered. The COVID-19 outcomes vary from asymptomatic infections and other mild cases to more severe cases that come with a wide variety of symptoms (e.g., fever, coughing, and trouble breathing). Compared with mild cases, more severe cases, such as hospitalization, admission to intensive care units, and death, will cause greater social and economic loss and overwhelm healthcare systems. Therefore, differentiating COVID-19 outcomes by its severity has important implications for risk assessment, resource allocation, and intervention strategies.

Another aspect that remains largely unexplored is how the associations between greenness and COVID-19 outcomes vary by socioeconomic and demographic groups, which raises the issue of environmental health inequality. Many environmental hazards (e.g., poor air quality, extreme heat events, and hazardous waste facilities) and environmental amenities (e.g., greenspace, and park) are often unequally distributed across geographical areas and social groups (Harlan and Ruddell, 2011; Hughey et al., 2016). It has long been recognized that these environmental inequalities often disproportionately or unfairly affected disadvantaged and underprivileged groups (e.g., low-income residents, and minorities). They tend to be segregated into neighborhoods with greater exposure to environmental hazards and less access to environmental amenities (Morello-Frosch and Lopez, 2006). Additionally, the inequality and inequity in environmental factors have the potential to translate into inequalities in a variety of health outcomes, including infectious diseases. Specific to COVID-19, we have identified two studies that demonstrate that greenness benefits Black residents more than their White counterparts in terms of COVID-19 infection rate (Lu et al., 2021) and mortality (Klompmaker et al., 2021). Whether such differentiated associations exist across other dimensions (e.g., age, gender, and geographic location), and to what extent greenness could ameliorate health inequity are unclear. Considering the long-lasting health inequalities in the US (Williams et al., 2019) and the disproportionate burden that the COVID-19 pandemic has put on disadvantaged and marginalized groups (Carrión et al., 2021), the equity consequence of greenness merits further examination. This is particularly important for future greening initiatives and policies.

To make reliable inference about the association between greenness and COVID-19 risk and inform future greening policies, this study employed COVID-19 Case Surveillance Data from the Centers for Disease Control and Prevention (CDC) that includes attributes of demographics, geography, date, disease outcomes and severity indicators. We represented availability of greenness as the population-density-weighted normalized difference vegetation index (PDW-NDVI) in Fig. 1b (see the details in the Methods section). We estimated the associations between availability of greenness and COVID-19 outcomes across the urban–rural continuum gradient (3,040 counties in the conterminous US) that cover the early, moderate, and peak periods of the pandemic (Jan 2020 to April 2021) using generalized additive models with a negative binomial distribution. Stratified analyses were performed by gender, race and age groups to reveal how the greenness-COVID-19 associations vary by sociodemographic status. The findings of this study have important implications for developing nature-based solutions and interventions to reduce health risk and inequity, and for post-pandemic recovery and future public health crises.

2. Methods

2.1. Study site.

Our study site contained 3,040 counties of the conterminous United States (68 counties were excluded due to data missing). We classified all the counties into six categories (Fig. 1a), namely large central metro, large fringe metro, medium metro, small metro, micropolitan, and

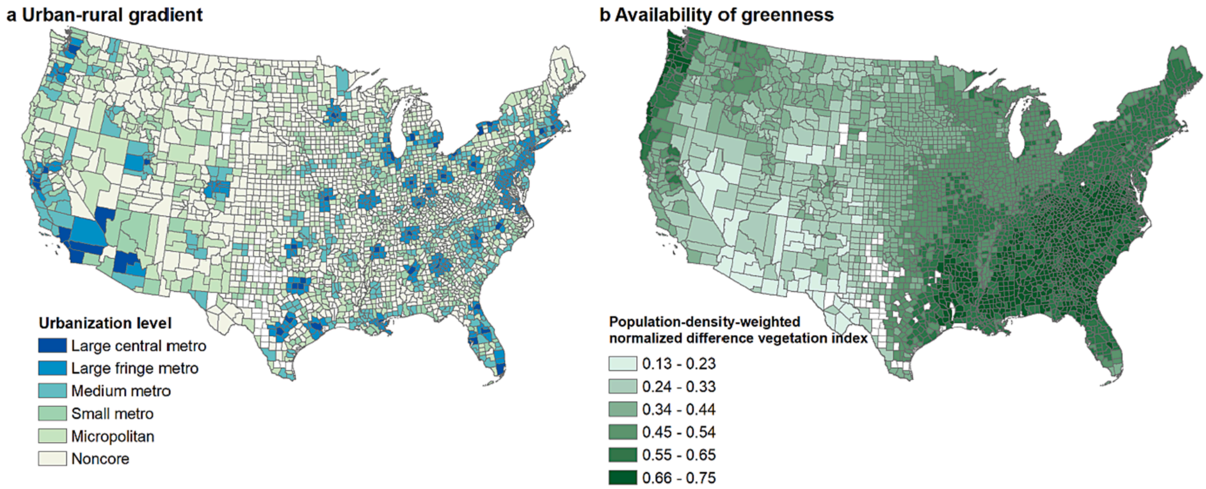

Fig. 1. Spatial distributions of six-level urban–rural continuum gradient and availability of greenness across the conterminous US.

noncore, according to the 2013 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme (Ingram and Franco, 2014). The definitions for the six categories could be found in Ref (Ingram and Franco, 2014). The six-level urban–rural continuum gradient under the 2013 NCHS scheme could separate metropolitan from nonmetropolitan counties, and separate large fringe metro from inner cities and suburbs of large metropolitan areas. Therefore, it is well-suited for health analyses to examine health disparities across the full urban–rural spectrum, and the impact of urbanization level on health outcomes (Ingram and Franco, 2012; Matthews et al., 2017).

2.2. COVID-19 data.

We requested and obtained the COVID-19 Case Surveillance Restricted Access Detailed Data at the county scale from the Centers for Disease Control and Prevention (CDC) on May 11, 2021 (retrieved at htt

Table 1
The distributions of COVID-19 infections, hospitalizations, and deaths for the conterminous United States, and for different sociodemographic groups.

	Urban				Rural	
	Large central metro	Large fringe metro	Medium metro	Small metro	Micropolitan	Noncore
Number of counties	68	366	363	351	634	1258
Number of infections	7,801,627 (32.2 %)	6,164,993 (25.4 %)	4,874,660 (20.1 %)	2,155,425 (8.9 %)	1,965,887 (8.1 %)	1,286,025 (5.3 %)
Sex						
Female	4,023,794 (32.2 %)	3,170,940 (25.4 %)	2,537,244 (20.3 %)	1,109,739 (8.9 %)	1,011,188 (8.1 %)	649,034 (5.2 %)
Male	3,697,698 (32.4 %)	2,926,730 (25.6 %)	2,277,416 (19.9 %)	1,013,449 (8.9 %)	919,360 (8.0 %)	592,069 (5.2 %)
Age, years						
0–19	1,194,852 (31.4 %)	1,007,794 (26.5 %)	788,624 (20.7 %)	337,951 (8.9 %)	294,276 (7.7 %)	185,065 (4.9 %)
20–39	2,955,625 (35.0 %)	2,060,606 (24.4 %)	1,708,144 (20.2 %)	736,878 (8.7 %)	630,814 (7.5 %)	363,509 (4.3 %)
40–59	2,265,828 (32.1 %)	1,888,600 (26.7 %)	1,381,151 (19.6 %)	589,371 (8.3 %)	565,963 (8.0 %)	372,030 (5.3 %)
>= 60	1,362,569 (28.9 %)	1,178,150 (25.0 %)	953,290 (20.2 %)	445,253 (9.4 %)	449,505 (9.5 %)	331,563 (7.0 %)
Race						
Non-Hispanic White	1,556,184 (20.6 %)	1,726,575 (22.9 %)	1,765,194 (23.4 %)	912,537 (12.1 %)	929,070 (12.3 %)	648,892 (8.6 %)
People of color	3,679,181 (48.8 %)	1,553,570 (20.6 %)	1,366,193 (18.1 %)	450,234 (6.0 %)	330,019 (4.4 %)	166,763 (2.2 %)
Number of hospitalizations	488,744 (42.2 %)	253,477 (21.9 %)	205,130 (17.7 %)	81,317 (7.0 %)	77,793 (6.7 %)	53,023 (4.6 %)
Sex						
Female	231,825 (42.2 %)	119,904 (21.8 %)	98,392 (17.9 %)	38,383 (7.0 %)	36,769 (6.7 %)	24,033 (4.4 %)
Male	255,736 (42.4 %)	132,320 (22.0 %)	105,597 (17.5 %)	42,249 (7.0 %)	39,787 (6.6 %)	27,134 (4.5 %)
Age, years						
0–19	12,720 (43.8 %)	6791 (23.4 %)	5147 (17.7 %)	1865 (6.4 %)	1591 (5.5 %)	946 (3.3 %)
20–39	68,878 (48.5 %)	31,130 (21.9 %)	23,070 (16.2 %)	8525 (6.0 %)	6684 (4.7 %)	3718 (2.6 %)
40–59	134,528 (45.0 %)	66,817 (22.4 %)	50,021 (16.7 %)	18,953 (6.3 %)	17,298 (5.8 %)	11,064 (3.7 %)
>= 60	272,426 (39.6 %)	148,320 (21.6 %)	126,517 (18.4 %)	51,721 (7.5 %)	51,714 (7.5 %)	36,424 (5.3 %)
Race						
Non-Hispanic White	124,205 (27.4 %)	107,814 (23.8 %)	98,942 (21.9 %)	43,017 (9.5 %)	46,568 (10.3 %)	32,204 (7.1 %)
People of color	290,607 (57.6 %)	90,358 (17.9 %)	75,160 (14.9 %)	23,392 (4.6 %)	15,924 (3.2 %)	9303 (1.8 %)
Number of deaths	166,003 (37.0 %)	103,633 (23.1 %)	84,269 (18.8 %)	35,384 (7.9 %)	34,521 (7.7 %)	25,365 (5.6 %)
Sex						
Female	72,834 (35.7 %)	48,557 (23.8 %)	39,170 (19.2 %)	16,081 (7.9 %)	16,134 (7.9 %)	11,365 (5.6 %)
Male	92,841 (38.4 %)	54,515 (22.5 %)	44,571 (18.4 %)	18,953 (7.8 %)	17,873 (7.4 %)	13,087 (5.4 %)
Age, years						
0–19	228 (34.3 %)	226 (34.0 %)	116 (17.5 %)	33 (5.0 %)	37 (5.6 %)	24 (3.6 %)
20–39	3398 (45.6 %)	1680 (22.5 %)	1206 (16.2 %)	476 (6.4 %)	398 (5.3 %)	300 (4.0 %)
40–59	21,514 (45.7 %)	9695 (20.6 %)	7636 (16.2 %)	3216 (6.8 %)	2866 (6.1 %)	2152 (4.6 %)
>= 60	140,830 (35.8 %)	91,887 (23.4 %)	75,171 (19.1 %)	31,560 (8.0 %)	31,020 (7.9 %)	22,439 (5.7 %)
Race						
Non-Hispanic White	55,000 (25.1 %)	56,361 (25.7 %)	48,947 (22.3 %)	21,048 (9.6 %)	22,063 (10.1 %)	15,926 (7.3 %)
People of color	85,597 (57.5 %)	26,969 (18.1 %)	21,487 (14.4 %)	7053 (4.7 %)	4499 (3.0 %)	3206 (2.2 %)

ps://data.cdc.gov/). The database is updated to April 2021 when we retrieved it. It contained 32 patient-level variables that cover various aspects of demographics, geography, date, disease outcomes and severity indicators, exposure history, presence of any underlying medical conditions and risk behaviors, and presence of symptoms (e.g., fever, diarrhea, cough, and abdominal pain) in the US. The detailed variable can be found on the COVID-19 case report form.

(https://www.cdc.gov/coronavirus/2019-ncov/downloads/pui-form.pdf). For our study, we obtained the age, gender, race and ethnicity, hospitalization status, death status, county of residence, and infection date for each patient, and aggregated all the information at the county level (Table 1).

2.3. Availability of greenness.

We obtained the moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) product (MOD13A3, version 6) for the US in 2020. The product has a monthly temporal resolution and a spatial resolution of 1 km, which is sufficient for our county-level analyses. The NDVI ranges from −1 to 1, with higher values associated with denser and greener vegetation cover. Although the NDVI is one of the most frequently employed vegetation indices in environmental health studies, it has two limitations. First, the NDVI does not distinguish among trees, shrubs, and grasses, nor do they speak to different natures of vegetation such as those in private residential land vs publicly accessible green land. Second, the NDVI technically is a measure of greenness provision, which only captures the coverage and distribution of greenness. When employed in exposure assessment, this widely used index does not consider accessibility to people who might use greenspace (Chen et al., 2022). To overcome this limitation, we employed the population-density-weighted average concentration, following the environmental health literature (Shakor et al., 2020; Tessum et al., 2021). For example, the population-density-weighted fine particulate matter, which assigns higher weights to the air pollution experienced where most people live, was employed by Tessum et al. (2021) as a proxy for air pollution exposure. The population-density-weighted vegetation index was also employed as a refined measurement when examining the associations between greenness and health outcomes (Lee et al., 2021; Xue et al., 2019). In this study, we employed spatially explicit remote sensing data to calculate population-density-weighted NDVI (PDW-NDVI) (Fig. 1b). Specifically, we multiplied the NDVI and population density at each cell (1 km by 1 km), summed all the values across the cells in the county, and then divided by the corresponding population density to yield the population-density-weighted NDVI for each county:

$$\text{PDW-NDVI} = \frac{\sum NDVI^{*}Pop\_den}{\sum Pop\_den} \quad (1)$$

where NDVI and pop_den were at a resolution of 1 km by 1 km, and they were derived from the MOD13A3 product and the 2020 Gridded Population of the World, from the Application for Extracting and Exploring Analysis Ready Samples: https://lpdaacsvc.cr.usgs.gov/appeears/. Although this approach does not take into account the detailed characteristics of spatial interaction between greenness and people, it improves the current approach in the greenness-COVID-19 literature that directly employs NDVI (Klompmaker et al., 2021; Spotswood et al., 2021). By assigning weights based on population densities, we assumed that high population density indicated a high probability of greenspace visits, and thus minimized the impact of the non-residential greenness such as wildland and cropland (Fig. 2).

2.4. Covariates.

A variety of covariates can affect COVID-19 outcomes, including environmental factors, socioeconomic status, demographics, and pre-existing health conditions (Klompmaker et al., 2021; Lu et al., 2021; Ma et al., 2021). To isolate and identify the impacts of greenness, it is important to adjust these effects in our analyses. The environmental factors considered for this study include annual average PM2.5 concentration and annual average temperature. The socioeconomic variables include income-related variables (e.g., median household income, and poverty rate), income inequality, and employment status. The demographic variables include age-related (e.g., the elderly, and young people), education-related, sex-related, race-related, and if residents have language barriers. The variables that indicate living conditions include homeownership, average house size, housing with severe problems or cost burden, children in single-parent households, social associations, and access to healthy foods. The indicators of pre-existing health conditions include general health statuses, physical distress, mental distress, obesity, diabetes prevalence, physical inactivity, and alcohol and tobacco use. Overall, a total of 36 covariates were considered for this study, and their statistical summary and description were presented in Supplementary Table 1. The variables were mainly downloaded from the US Census Bureau 5-year American Community Survey (https://www.census.gov/programs-surveys/acs), the County Health Ranking & Roadmaps (https://www.countyhealthrankings.org/), and the National Centers for Environmental Information (https://www.ncei.noaa.gov/).

2.5. Statistical analyses.

We used generalized additive models with a negative binomial distribution to examine associations between PDW-NDVI and COVID-19 outcomes. We employed counties as the basic unit of analysis due to that (1) it is the fundamental administrative unit in the United States; and (2) it is frequently employed in environmental health research (Anderson et al., 2015; Matthews et al., 2017) and previous COVID-19 studies (Klompmaker et al., 2021; Lu et al., 2021; Russette et al., 2021). All the statistical analyses were performed using R software (version 4.1.1) with the packages “mgcv” and “gstat”. To examine the

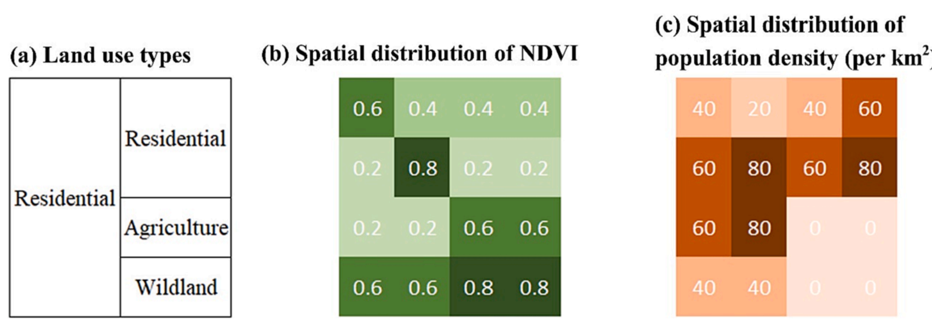

Fig. 2. A hypothetical example for calculating population-density-weighted NDVI average (which was 0.38 in this case). For example, 0.8 (row 4, column 4) in the middle panel was ignored because the corresponding population density cell in the right panel was 0, while 0.2 (row 2, column 4) in the middle panel was assigned a high weight because the population density in this cell was high.

robustness of the greenness-COVID-19 associations, we built regression models with increased levels of adjustments, and there were 4 models for each COVID-19 outcome. The first model was the unadjusted one that included only PDW-NDVI (Eq (2)). The second model was the minimally adjusted model which also included two other environmental variables: temperature and PM2.5 (Eq (3)). The third model further introduced socioeconomic-demographic variables and indicators of living conditions (Eq (4)). The last model (Model 4: Eq (5)) was the fully adjusted one that included indicators of pre-existing health conditions and all explanatory variables in Model 3. The four models were expressed as:

$$Y_i \sim Negative\ Binomial(E(Y_i))$$

$$\text{Model 1: } \log(\mathrm{E(Yi)}) = \alpha + \beta_1 \mathrm{PDW\text{-}NDVI_i} + \mathrm{re(county_i)} + \mathrm{tps(lat_i, long_i)} + \mathrm{offset(log(pop))} \tag{2}$$

$$\text{Model 2: } \log(\mathrm{E(Yi)}) = \alpha + \beta_1 \mathrm{PDW\text{-}NDVI_i} + \beta_2 \mathrm{Environment_i} + \mathrm{re(county_i)} + \mathrm{tps(lat_i, long_i)} + \mathrm{offset(log(pop))} \tag{3}$$

$$\text{Model 3: } \log(\mathrm{E(Yi)}) = \alpha + \beta_1 \mathrm{PDW\text{-}NDVI_i} + \beta_2 \mathrm{Environment_i} + \beta_3 \mathrm{Socioeconomic_i} + \mathrm{re(county_i)} + \mathrm{tps(lat_i, long_i)} + \mathrm{offset(log(pop))} \tag{4}$$

$$\text{Model 4: } \log(\mathrm{E(Yi)}) = \alpha + \beta_1 \mathrm{PDW\text{-}NDVI_i} + \beta_2 \mathrm{Environment_i} + \beta_3 \mathrm{Socioeconomic_i} + \beta_4 \mathrm{Health_i} + \mathrm{re(county_i)} + \mathrm{tps(lat_i, long_i)} + \mathrm{offset(log(pop))} \tag{5}$$

where Y_i is the observed count of COVID-19 outcomes (e.g., infections, hospitalizations, or deaths) in county i; $E(Y_i)$ is the expected count in county i; α is the intercept; β_1 represents the log-relative risk of COVID-19 outcomes (e.g., infection rate, hospitalization rate, or mortality rate) associated with a 0.01 increase of PDW-NDVI at county i; β_2 is the coefficient for environmental variables (e.g., temperature, and PM2.5); β_3 is the coefficient for socioeconomic-demographic variables and indicators of living conditions; β_4 is the coefficient for indicators of pre-existing health conditions. When covariates had Pearson's correlation values greater than 0.7, only one was selected to reduce the potential multicollinearity issue (Meyers et al., 2016) (see the correlation matrix in Supplementary Fig. 1). We also performed a collinearity diagnostic using the variance inflation factor (VIF) to confirm that the multicollinearity problem was not a concern for this study (Supplementary Table 2).

For all regression models, we included three terms which are explained below. The term "$re(county_i)$" represents a random effect of the county to account for county-specific contexts that are not captured by the models (e.g., COVID related policies, and unmeasured variability for county-level characteristics) (Sera et al., 2021; Spotswood et al., 2021). The term "$tps(lat_i, long_i)$" represents a two-dimensional thin-plate spline function that is parameterized based on the county coordinates (Xue et al., 2019); we followed ref (Ma et al., 2021) to employ a thin plate spline with a maximum of 200 knots to control spatial autocorrelation. The last term in the Models 1–4 is "offset(log(pop))", which employs the county population at the log scale as an offset term. The offset term has a coefficient of 1 so that it can be theoretically moved back to the left side of the equation to turn the count estimator into a rate (Zuur et al., 2009). This practice is frequently used in previous environmental health studies (Russette et al., 2021). Note that when the dependent variable is COVID-19 hospitalizations or deaths, we employed the "offset(log(infection))" (the log scale of the total infection in a county) as an offset term, in this way we look at the proportions of hospitalizations or deaths out of all infection cases and could better differentiate the severity of the disease from its prevalence. We also performed additional sensitivity analyses by employing the offset term "offset(log(pop))". For instance, the death-to-case ratio is typically referred to as the case fatality rate, while the death-to-population ratio is the case mortality rate (Cao et al., 2020). In our main models, we employed "offset(log(infection))" because it is a measure of the severity of the condition, while the "offset(log(pop))" was also used for a robust check. The diagnostics information for the models was shown in Supplementary Fig. 2 and 3.

To examine variations in the associations between PDW-NDVI and COVID-19 outcomes across the urban–rural continuum gradient, we introduced dummy variables for six urbanization levels in the models. The variations were examined using interactions terms between the dummy variables and PDW-NDVI. To evaluate disparate associations between availability of greenness and different sociodemographic groups, we stratified all the analyses by gender, two racial groups (Non-Hispanic White vs People of color), and four age groups (0–19 years, 20–39, 40–59, and ≥ 60). In addition, we also stratified the analyses by four periods: Period 1 from March 1, 2020, to May 31, 2020; Period 2 from June 1, 2020 to August 31, 2020; Period 3 from September 1, 2020, to November 30, 2020; and Period 4 from December 1, 2020, to February 28, 2021. These four periods were associated with four seasons and roughly correspond to different stages of COVID-19 transmissibility.

For hospitalizations and deaths, we did not include all the counties in our analyses due to the data missing. In the COVID-19 database of the CDC, the hospitalization and death statuses associated with each infected patient were "Yes", "No", "Missing", and "Unknown". Based on the attribute values of hospitalization and death statuses, we calculated the percentages of confirmed statuses [(Yes + No)/(Yes + No + Missing + Unknown)] for each county and limited our analyses to the counties that have a majority of the confirmed cases (≥50 %). Despite this limitation, our statistical power analysis showed that we had enough sample size to reveal the associations between availability of greenness and COVID-19 severity (see the details in the Supplementary materials). In addition, we also conducted sensitivity analysis (with the percentages of confirmed statuses from 50 %, to 60 %, and to 70 %) to examine the robustness of the results. The sensitivity analyses showed the same conclusions as the main models, and therefore their results were not displayed here.

3. Results

3.1. Summary statistics

From January 2020 to April 2021, there were a total of 24,248,617 COVID-19 infections, 1 159,484 hospitalizations, and 449,175 deaths in the 3,040 counties across the conterminous US (Table 1). Of the three COVID-19 outcomes examined in this study, they all displayed decreased patterns across the urban–rural gradient, with the highest numbers reported in the large central metro area and the lowest numbers in the noncore area. As a result, the urban counties had a large majority of cases when compared with their rural counterparts. As for the temporal trend, the study period was divided into four periods, which were associated with four seasons and roughly correspond to different stages of COVID-19 transmissibility (Fig. 3). The infection cases experienced an early growth (Period 1), and then the first peak (Period 2), followed by a subsequent rapid increase (Period 3) until the second peak (Period 4) (Fig. 3d). The outcomes for hospitalizations and deaths displayed a similar temporal pattern with the infection cases, except that the formers also reached the peak level in Period 1 (Fig. 3e and Fig. 3f).

Regarding the distribution of COVID-19 outcomes among different sociodemographic groups, the COVID-19 prevalence outcomes (e.g., infections) displayed different patterns when compared to the COVID-19

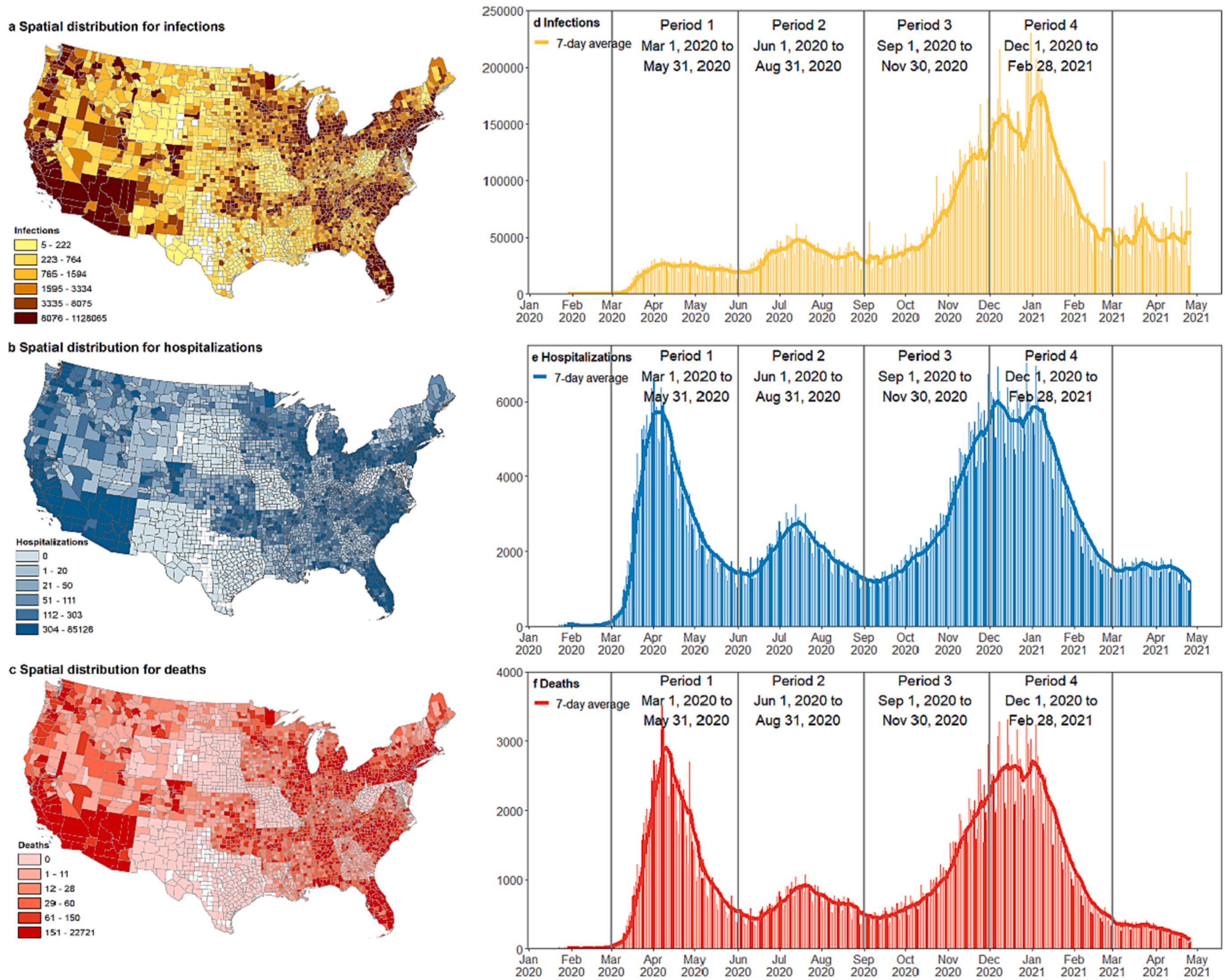

Fig. 3. Spatial and temporal distributions of COVID-19 infections, hospitalizations, and deaths from January 2020 to April 2021.

severity outcomes (e.g., hospitalizations and deaths) (Table 1). We found that more females were infected with COVID-19 than males, while the opposite was observed for COVID-related hospitalizations and deaths. A similar pattern was also identified among different age groups. COVID-19 infection took a disproportionate toll on adults (age groups 20–39 and 40–59), with a percentage being 64.6 %. Although the elderly (age >= 60) only occupied 19.6 % of infection cases, they comprised 59.4 % and 87.7 % of COVID-related hospitalizations and deaths, respectively. As for the racial groups, the distributions for the infections and hospitalizations were roughly equal among white Americans and people of color (POC), while the death toll for the former was approximately 20 % higher than the latter. This is probably due to different age structures: the most common age for white Americans is more than double that of POC (Schaeffer, 2019).

3.2. *The associations between availability of greenness and COVID-19 outcomes.*

We found that the COVID-19 infection rate was statistically significant and negatively associated with availability of greenness (Table 2). This negative association was pretty robust, regardless of the model settings (e.g., unadjusted, adjusted by several covariates, and fully adjusted models). As for the magnitude, the percentage decrease for COVID-19 infection rate associated with a 0.01 increase in PDW-NDVI changed from 1.13 (95 % confidence interval [CI]: 0.49–1.78) in the unadjusted model to 0.80 (CI: 0.07–1.53) in the fully adjusted model.

Regarding the COVID-19 hospitalization and fatality rates, we found they were statistically unrelated to availability of greenness (Tables 3 and 4). These null relationships for COVID hospitalization and fatality rates remained the same across the unadjusted to fully adjusted models, and when changing the offset term from “offset(log(infection))” to“offset(log(pop))”. This suggests the absence of any association between greenness and indicators of COVID-19 severity.

3.3. *Disparities for the greenness-COVID-19 associations.*

Here we only displayed the disparate associations for COVID-19 infection rates (Fig. 4), as the COVID-19 hospitalization and fatality rates showed null relationships with availability of greenness. We found that there were statistical and negative associations between availability of greenness and COVID-19 infection rates in the noncore, micropolitan, small and medium metros. The percentage decrease for COVID-19 infection rate associated with a 0.01 increase in PDW-NDVI were at a similar level for all these areas, varying from 1.13 (CI: 0.41–1.85) for the noncore to 1.64 (CI: 0.85–2.42) for the micropolitan. Regarding the disparities across different periods, negative associations were observed

Table 2
Results of models that examine the associations between availability of greenness and COVID-19 infections.

	COVID-19 Infections			
	Model 1	Model 2	Model 3	Model 4
PDW-NDVI[a]	−1.13 (-1.78, −0.49)***	−0.69 (-1.30, −0.08)*	−0.87 (-1.59, −0.14)*	−0.80 (-1.53, −0.07)*
Average Daily PM2.5		1.78 (-1.22, 4.87)	1.92 (-1.14, 5.07)	1.93 (-1.12, 5.08)
Average Temperature		4.27 (0.40, 8.29)*	3.37 (-0.49, 7.37)	4.29 (0.37, 8.36)*
% Unemployment			−3.39 (-6.07, −0.64)*	−3.08 (-5.77, −0.31)*
% poverty			−0.30 (-1.13, 0.54)	0.04 (-0.81, 0.90)
GINI			0.85 (-0.07, 1.77)	0.78 (-0.14, 1.70)
% not proficient in English			−1.75 (-3.15, −0.34)*	−1.89 (-3.30, −0.46)**
% Bachelor			−0.77 (-1.18, −0.36)***	−1.05 (-1.50, −0.59)***
% Females			−3.39 (-4.67, −2.09)***	−3.07 (-4.37, −1.76)***
% White			−1.20 (-1.53, −0.88)***	−1.37 (-1.71, −1.04)***
% 60 and older			−1.60 (-2.53, −0.67)***	−1.62 (-2.55, −0.67)***
% below 18			−1.33 (-2.64, 0)*	−1.15 (-2.47, 0.19)
% Rent			−0.66 (-1.22, −0.09)*	−0.69 (-1.25, −0.12)*
Average house size			−8.57 (−22.46, 7.81)	−9.50 (−23.26, 6.73)
% Severe housing problems			0.25 (-0.80, 1.31)	0.12 (-0.93, 1.18)
% Children in single-parent households			−0.17 (-0.61, 0.28)	−0.17 (-0.62, 0.27)
% Limited access to healthy foods			0.01 (-0.33, 0.36)	0.03 (-0.32, 0.37)
Social associations			0.93 (0.40, 1.46)***	0.92 (0.39, 1.46)***
% Adult obesity				−0.35 (-0.92, 0.22)
% Adult diabetes				−0.53 (-1.39, 0.34)
% Physical inactivity				−0.08 (-0.70, 0.55)
% Access to exercise				0.02 (-0.11, 0.16)
% Excessive drinking				2.59 (0.89, 4.32)**

*Significant at $p < 0.05$.
**Significant at $p < 0.01$.
***Significant at $p < 0.001$.
[a] population-density-weighted normalized difference vegetation index.

for all periods except for Period 4, although Period 4 was the peak stage of the pandemic. When disaggregating the population into different sociodemographic groups, we found that the availability of greenness was negatively associated with COVID-19 infection rates for males and people aged 40 years or younger, while statistically unrelated for females and the elderly. In contrast, for both White residents and POC, the greenness-COVID-19 associations were non-significant.

Table 3
Results of models that examine the associations between availability of greenness and COVID-19 hospitalizations.

	COVID-19 Hospitalization			
	Model 1	Model 2	Model 3	Model 4
PDW-NDVI[a]	0.06 (-0.46, 0.58)	0.12 (-0.40, 0.65)	−0.10 (-0.67, 0.46)	−0.08 (-0.64, 0.49)
Average Daily PM2.5		0.26 (-2.14, 2.71)	0.21 (-2.12, 2.59)	0.39 (-1.94, 2.77)
Average Temperature		3.29 (0.33, 6.33)*	2.08 (-0.69, 4.93)	1.96 (-0.82, 4.82)
% Unemployment			1.03 (-1.18, 3.29)	0.71 (-1.51, 2.97)
% poverty			−0.64 (-1.34, 0.07)	−0.57 (-1.29, 0.16)
GINI			0.71 (-0.10, 1.53)	0.76 (-0.05, 1.57)
% not proficient in English			−1.85 (-3.17, −0.51)**	−1.42 (-2.76, −0.06)*
% Bachelor			−0.93 (-1.27, −0.58)***	−0.60 (-1.01, −0.19)**
% Females			1.68 (0.43, 2.94)**	1.64 (0.38, 2.91)*
% White			−0.82 (-1.10, −0.54)***	−0.81 (-1.09, −0.52)***
% 60 and older			1.79 (1.00, 2.59)***	1.70 (0.91, 2.50)***
% below 18			1.72 (0.50, 2.96)**	1.63 (0.41, 2.87)**
% Rent			−0.08 (-0.59, 0.43)	−0.04 (-0.56, 0.48)
Average house size			−16.78 (-29.19, −2.21)*	−14.81 (-27.48, 0.08)
% Severe housing problems			0.04 (-0.90, 0.98)	0.18 (-0.75, 1.13)
% Children in single-parent households			0.05 (-0.34, 0.45)	0.00 (-0.40, 0.40)
% Limited access to healthy foods			−0.09 (-0.41, 0.23)	−0.06 (-0.38, 0.27)
Social associations			0.23 (-0.28, 0.73)	0.23 (-0.27, 0.73)
% Adult obesity				0.39 (-0.12, 0.90)
% Adult diabetes				0.88 (0.10, 1.66)*
% Physical inactivity				0.64 (0.08, 1.19)*
% Access to exercise				0.02 (-0.10, 0.14)
% Excessive drinking				2.01 (0.59, 3.45)**

*Significant at $p < 0.05$.
**Significant at $p < 0.01$.
***Significant at $p < 0.001$.
[a] population-density-weighted normalized difference vegetation index.

4. Discussion

4.1. The associations between availability of greenness and COVID-19 prevalence and severity

In summary, we developed the generalized additive models by using the COVID-19 data, PDW-NDVI, and socioeconomic and environmental variables. After controlling for potential covariates and accounting for spatial dependence in the models, we assessed the associations between availability of greenness and COVID-19 prevalence and severity, examined how the associations varied across the urban–rural gradient and different periods and estimated the disparate associations for different sociodemographic groups. We found that the associations

Table 4
Results of models that examine the associations between availability of greenness and COVID-19 deaths.

	COVID-19 Mortality			
	Model 1	Model 2	Model 3	Model 4
PDW-NDVI[a]	−0.11 (-0.73, 0.52)	0.04 (-0.59, 0.68)	−0.42 (-1.11, 0.28)	−0.46 (-1.15, 0.23)
Average Daily PM2.5		−1.38 (-4.03, 1.35)	−0.66 (-3.27, 2.03)	−0.69 (-3.28, 1.97)
Average Temperature		5.64 (1.90, 9.51)**	5.51 (1.90, 9.24)**	4.42 (0.83, 8.14)*
% Unemployment			0.99 (-1.75, 3.80)	1.05 (-1.68, 3.86)
% poverty			0.40 (-0.51, 1.33)	−0.02 (-0.95, 0.92)
GINI			1.00 (-0.06, 2.07)	1.04 (-0.01, 2.10)
% not proficient in English			−0.98 (-2.64, 0.71)	−0.97 (-2.64, 0.73)
% Bachelor			−0.70 (-1.13, −0.27)**	−0.37 (-0.88, 0.14)
% Females			0.14 (-1.45, 1.74)	−0.34 (-1.92, 1.26)
% White			−0.26 (-0.61, 0.10)	−0.01 (-0.37, 0.36)
% 60 and older			2.80 (1.78, 3.82)***	2.63 (1.61, 3.65)***
% below 18			2.55 (1.06, 4.07)***	2.48 (0.99, 3.99)**
% Rent			0.14 (-0.50, 0.78)	0.17 (-0.47, 0.82)
Average house size			−20.58 (-35.89, −1.63)*	−21.31 (-36.46, −2.56)*
% Severe housing problems			−0.83 (-1.98, 0.33)	−0.74 (-1.89, 0.42)
% Children in single-parent households			−0.01 (-0.53, 0.51)	−0.03 (-0.55, 0.49)
% Limited access to healthy foods			0.03 (-0.41, 0.46)	−0.01 (-0.43, 0.43)
Social associations			0.19 (-0.44, 0.82)	0.21 (-0.42, 0.84)
% Adult obesity				−0.38 (-1.01, 0.25)
% Adult diabetes				1.21 (0.23, 2.19)*
% Physical inactivity				0.52 (-0.18, 1.22)
% Access to exercise				0.01 (-0.13, 0.16)
% Excessive drinking				−3.41 (-5.08, −1.70)***

*Significant at $p < 0.05$.
**Significant at $p < 0.01$.
***Significant at $p < 0.001$.
[a] population-density-weighted normalized difference vegetation index.

between availability of greenness and COVID-19 infection rates were statistically significant and negative. This finding is encouraging, even though there are null findings between availability of greenness and COVID-19 hospitalization and fatality rates. Previous studies that examined the relationships between greenness and COVID-19 outcomes also obtained similar findings, regardless of different periods, study sites, and greenness measures (Table 5). For example, Klompmaker et al. (2021) reported that higher values of the NDVI were associated with lower COVID-19 infection rates across the 2,297 counties in the US, and Spotswood et al. (2021) obtained a similar conclusion when examining the associations between the NDVI and COVID-19 infections at the ZIP-code level in 17 states of the US. When measuring greenery by vegetation (You and Pan, 2020), forest cover (Jiang et al., 2021), and Google Street View (Nguyen et al., 2020), the negative associations remain consistent. The evidence on the relationship between greenness and COVID-19 infection seems to be robust. This is probably due to several mechanisms that human exposure to greenness affects physical health, mental health and well-being, with substantive evidence in the field of environmental health (Frumkin et al., 2017; Lu et al., 2021). In summary, greenness could improve environmental quality and living standard by providing a wide range of benefits such as heat reduction, noise reduction, air pollution removal, water purification, and conservation of energy consumption (Lin et al., 2019). These benefits of greenness exposure, collectively referred to as “ecosystem services” (Bratman et al., 2019), could directly contribute to human well-being. In addition, greenness could act as a catalyst to facilitate the changes in behaviors and lifestyles from sedentary behaviors to more outdoor physical activities and from socially isolated to active community engagement, both of which are more conducive to physical and mental health (Dadvand et al., 2016; Kuo, 2015). Markevych et al. (2017) and Marselle et al. (2021) summarize the above health effects of greenness through four pathways: reducing harm, restoring capacities, building capacities, and causing harm. Lastly, greenness and the associated activities are typically in outdoor settings, which makes social distancing more likely and may lead to low virus concentrations due to larger physical space and natural air movement. This is particularly important for COVID-19 that is spread through the airborne transmission of respiratory viruses (Jiang et al., 2021; Spotswood et al., 2021).

Compared with most studies that focus on the associations between greenness and COVID-19 infection rates, relatively less attention has been paid to the severity of COVID-19 outcomes. We identified three studies that examined the associations between greenness and COVID-19 deaths (Klompmaker et al., 2021; Lee et al., 2021; Russette et al., 2021), and fewer studies that focused on other severity indicators of COVID-19 outcomes (e.g., hospitalizations, symptoms, and admissions to Intensive Care Units). Our study found that availability of greenness was statistically unrelated to both COVID-19 hospitalization and fatality rates, regardless of adjusting for covariates or not, urban–rural gradients, and different periods. Unlike COVID-19 infections that show consistent and negative associations with greenness, the evidence for COVID-19 deaths is mixed and varies across studies. Among the three studies we identified, Klompmaker et al. (2021) reported that there existed null relationships between greenness and COVID-19 mortality, Russette et al. (2021) showed negative associations for some counties while no associations for the remaining counties, and Lee et al. (2021) observed negative associations. These conflicting results could reflect different greenness indexes and methodological approaches that were adopted, or different locations and time periods that were considered. Another implication is that all three studies calculated COVID-19 mortality rates, which reference the death counts to the total population. This calculation is not able to differentiate the severity of the COVID-19 disease (e.g., death-to-case ratio) from the COVID-19 infection (e.g., case-to-population ratio). The effect of greenness on COVID-19 severity might be masked or moderated by the association between greenness and COVID-19 infection, as more COVID-19 infection cases would be more likely to be associated with more COVID-19 death counts. Nevertheless, our fatality rates didn’t reveal statistically significant associations between availability of greenness and COVID-19 severity indicators. More research is needed in the future to make a conclusive statement.

4.2. Disparities for the greenness-COVID-19 associations and their inequity implications

We found that the percentage decreases for the COVID-19 infection rates were significantly associated with higher availability of greenness across all urban–rural gradients and periods, except for the large metros and Period 4. This is surprising as (1) we expect that in cities (especially

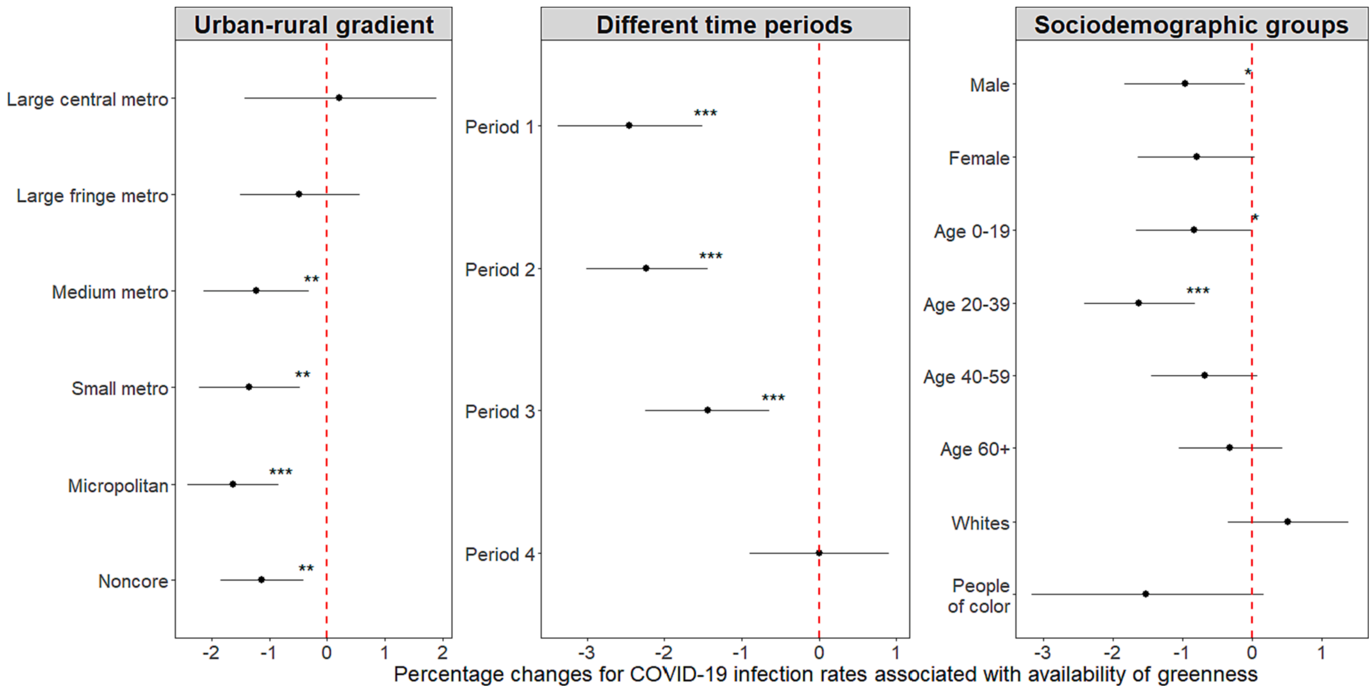

Fig. 4. The disparate associations between availability of greenness and COVID-19 infections. Graphs show point estimates with error bars for 95 % CIs, after adjusting for covariates listed in Table 2. Period 1 from March 1, 2020, to May 31, 2020; Period 2 from June 1, 2020, to August 31, 2020; Period 3 from September 1, 2020, to November 30, 2020; and Period 4 from December 1, 2020, to February 28, 2021. The significance levels of the associations are expressed as $p < 0.05$ (*), $p < 0.01$ (**), and $p < 0.001$ (***).

Table 5
Examples of statistical associations between greenness and COVID-19 outcomes.

	Spotswood et al. (2021)	Klompmaker et al. (2021)	Jiang et al. (2021)	Russette et al. (2021)	Nguyen et al. (2020)
Time periods	Up to Sept 30, 2020	Up to Jun 7, 2020	Up to Dec 31, 2020	Up to Jul 29, 2020	Up to Jun 21, 2020
Study sites	Urbanized areas in 17 states of US	2,297 counties in US	3,108 counties in US	3,049 counties in US	20 states in US
Scales	ZIP code scale	County level	County level	County level	ZIP code scale
greenness measures	NDVI and park proximity	NDVI	Six types of green spaces	Leaf Area Index	Google Street View
COVID-19 outcomes	Incidence	Incidence and mortality	Incidence	Mortality	Incidence
Associations between greenness and COVID-19	Negative	Negative for incidence, not significant for mortality	Negative	Negative for certain counties	Negative

in metropolitan areas), residents tend to be more closely interacting with nature because nature is integrated into the urban fabric with the support of high accessibility, park facilities, and other amenities (Fuertes et al., 2014; Klompmaker et al., 2021); and (2) the Period 4 has the highest infection numbers. This might be because metropolitan areas typically have more severe environmental inequity (Pearsall and Pierce, 2010; Wolch et al., 2014). The amount of greenness does not necessarily guarantee equitable access for various groups of people due to uneven vegetation distribution and private garden ownership. In addition, sociodemographic characteristics and COVID-19-related regulations (e.g., adherence to COVID-19 restrictions) may also vary spatially and lead to the different associations across urbanicity levels. For example, high population densities in metropolitan areas make it hard to maintain social distancing and may further prevent greenspace visits. The existing COVID-19-related studies tend to treat all urban areas as the same (Lee et al., 2021; Spotswood et al., 2021), but our study shows that the greenness-COVID-19 associations are different between large metro, and medium and small metros. Previous public health studies also show that it is necessary to conduct health analyses across the full urban–rural spectrum due to different environments and behavior patterns associated with different urbanization levels (Ingram and Franco, 2012; Matthews et al., 2017). As for the null relationship in Period 4, it could be more infectious variants in Period 4 that mask the relationship between availability of greenness and COVID-19 infection rates, or Period 4 tends to have cold weather that reduces people's greenspace visiting frequency and duration. While our study does not reveal the underneath mechanisms, we call for more future studies to examine the greenness-COVID-19 associations under various contexts and identify the circumstances in which greenness is/isn't associated with less COVID-19 infection rates.

Regarding the disparities across the sociodemographic dimensions, although availability of greenness is associated with the percentage decrease for the COVID-19 infection rate, it has limited effects in ameliorating COVID-19-related inequity. We found negative greenness-COVID-19 associations for males, the young and adults, while there were null relationships for females and older adults. This is especially a concern considering that the elderly occupied large proportions of hospitalizations and death tolls and were disproportionately affected by COVID-19 than any other age group (Table 1). We identified two studies that examine the equity implications of greenness for COVID-19. Lu et al. (2021) reported that higher greenness coverage indicates a lower racial disparity in COVID-19 infection rates based on the 135 most urbanized counties of the US. Spotswood et al. (2021) showed that underprivileged communities tend to be hardest hit by COVID-19 due to the widespread inequity in access to nature across urbanized areas in the US.

Several reasons might explain why greenness has limited equity impacts. First, natural disparities are prevalent, with disadvantaged subpopulations (e.g., low-income residents, and minorities) and vulnerable groups (e.g., young children and the elderly) often associated with less access to greenspace, lower tree cover, and fewer tree-derived ecosystem services than their advantaged and affluent counterparts (Gerrish and Watkins, 2018; Lin, Wang, & Li, 2021b; Nesbitt, Meitner, Girling, Sheppard, & Lu, 2019). Second, how people live, work, play, and interact with greenspace may aggregate the existing natural disparities. For example, the work-from-home policy may provide white workers with flexible work and discretionary time (Labib et al., 2021), and result in higher frequency and longer duration of greenspace visits (Astell-Burt and Feng, 2021). This is especially the case for people that have privately-owned gardens and backyards where they can enjoy nature and undertake the associated activities without worrying about COVID-19 exposure (Labib et al., 2021). For low-income people, especially essential workers in the service sector, exposure to nature seems to be a luxury due to several reasons, such as the need to be present in the workplace and they may need to travel further to reach greenspace. When examining other health outcomes, the health inequity remediation potential of greenness is uncertain in the literature, with the results varying by greenery measures (Frumkin et al., 2017), health outcomes (Mitchell and Popham, 2008), sociodemographic groups (Jennings and Gaither, 2015), and types of exposure and interactions (Bratman et al., 2019). More studies in the area are needed to help build ecologically vital and socially just communities.

4.3. Method considerations

COVID-19 is an infectious disease that implies the existence of a spatial process (e.g., near things are more related to each other than things that are further apart) and the violation of independence in traditional statistical tests (Zuur et al., 2009). Such violation could cause a biased estimation of error variance and lead to misleading significant tests and measures of model fits (Zhang et al., 2009). Although it is not a standard practice in current greenness-COVID studies, spatial autocorrelation is increasingly recognized and incorporated to ensure a robust inference about the greenness-COVID associations. This study simulates spatial autocorrelation by applying a thin plate spline to county coordinates. This method has the advantage of flexibility and does not require the specification of model forms and parameters. Therefore, it is also adopted by previous greenness-COVID research (Klompmaker et al., 2021; Ma et al., 2021), as well as other studies that examine the health benefits of greenness (Venter et al., 2022; Xue et al., 2019). Other commonly employed methods that account for the spatial autocorrelation include, but are not limited to, spatial regression models (e.g., spatial error, spatial lag, and spatial Durbin models) (Lin, Wang, & Huang, 2021a), mixed effect models with a random effect to control for the non-independence of data (Spotswood et al., 2021), models that explicitly specify spatial covariance structure (Zuur et al., 2009). As there is no one method that works for all contexts, researchers should choose an appropriate one based on their expertise and research questions.

When examining the associations between availability of greenness and COVID-19 severity, we included fewer counties due to missing data. This may raise concerns about the lack of statistical power. Statistical power is the probability of detecting an effect when such an effect exists, and it is mainly related to Type II error (Kraemer and Blasey, 2015). In practice, one common reason to conduct power analysis is to determine the necessary sample size to detect an effect of a given test (Cohen, 1992). Through power analysis (see the details in Supplementary materials), we concluded that our study had enough sample size to examine the relationships between greenness and COVID-19 severity. Despite this, we cannot exclude the possibility that our null findings on the relationship between greenness and COVID-19 severity could result from a lack of power due to several disadvantages of power analysis (e.g., the default significance and power level we adopted and several assumptions of power analysis) (Kraemer and Blasey, 2015). When conducting methodology design for future greenness-COVID studies, we recommend that future studies to (1) explicitly consider spatial autocorrelation, (2) conduct power analysis if there is any concern about the sample size, and (3) ensure the transparency of the modeling process to facilitate a more valid comparison for different modeling practices and results.

4.4. Greening policies for post-pandemic recovery and future public health crises

Although our studies, as well as previous studies, didn't infer causality between greenness and COVID-19 outcomes, green recovery still sounds appealing to the decision-makers and stakeholders (Geary et al., 2021; Kleinschroth and Kowarik, 2020) for several reasons. First, the studies that examine the greenness-COVID-19 associations have received great attention, with most studies reporting negative correlations between them (Table 5). The growing evidence suggests that greenness has important implications for post-pandemic recovery and future public health crises. Second, greenness has been linked to a variety of improved physical and mental health outcomes through multiple mechanisms and pathways (Bratman et al., 2019; Frumkin et al., 2017; James et al., 2015). These pathways might also play roles in the associations between greenness and COVID-19 outcomes (Spotswood et al., 2021). Third, greenness exposure is a cost-effective solution that residents have direct control. Among all the factors (Ma et al., 2021; Sera et al., 2021) that are associated with COVID-19 transmission and outcomes, greenness exposure is one of the very few factors that people have direct control over when comparing with other variables (e.g., air temperature, and humidity). For example, people could request tree planting or adopt a tree in their neighborhoods (Lin, 2020), volunteer in tree stewardship activities, or simply change their lifestyle and behavior patterns to have more greenspace visits. Additionally, residents could work with professional organizations to develop an appropriate planting scheme to support integrating greenness into their daily life.

Nevertheless, increases in nature exposure face a variety of challenges. First, there is evidence of declines in humans' interactions with nature (Bratman et al., 2019), and this is especially the case for urban residents. Urbanization pressures often reduce greenspace for the sake of other land uses, and current modern lifestyles (e.g., physical inactivity, increased screen time, and delivery of convenience food) often compete with outdoor activities such as playing in nature (Frumkin et al., 2017). Second, greenness under certain contexts can produce adverse effects or disservices. One well-known example is gentrification and displacement where poor residents are driven away due to an increase in property or rent values (Frumkin et al., 2017; Wolch et al., 2014). Third, greenness can be either an asset or a liability, depending on whether it is appropriately managed. For example, greenspace filled with trash and litter is often positively associated with fear of crime and crime activities (Kuo and Sullivan, 2001; Sreetheran and Van Den Bosch, 2014).

In view of the abovementioned challenges, future greening interventions for improving public health and ameliorating health inequity should be designed in integrated and inclusive ways. These include a variety of options covering the domains of infrastructure design, policy regulations, and urban planning. First, green and built infrastructure could be mixed and configured together to reduce land conflicts. Built infrastructure (e.g., road networks and walking paths) can increase access to greenspaces, while greening streets, green roofs and facades can enhance human exposure to greenness. Second, financial investment and policy regulations could be integrated together to enhance park visits. In addition to devoting resources to clean and green parks and increasing park facilities, greening policies and regulations should be designed to reduce the barriers to greenspace use and be inclusive and age-friendly such as dedicated park times for children and older adults (Labib et al., 2021). Third, future greening interventions should enhance citizen engagement and participatory planning through consulting with marginalized communities and incorporating their concerns. The concerns mentioned above (e.g., disservices, green gentrification, and fear of crime) may seriously discourage greenspace visits. How to engage city dwellers of diverse backgrounds through effective greening interventions merits further exploration. With improved greening planning and policies, we argue that nature exposure could play an even more important role in post-pandemic recovery and future public health crises.

4.5. Limitations and working hypotheses

To better inform future environmental health research, several limitations of the study should be noted. First, the location of individual COVID-19 patients is only available at the county level, and therefore we performed the analyses based on the unit of county. Such analyses made an implicit assumption of homogeneity within a county, which is unlikely to hold true. Future individual-level analyses, with careful design for privacy protection, are needed. Second, we simplified availability of greenness as the PDW-NDVI, which is insufficient to capture the full range of interactions between people and nature. The effects of nature exposure are moderated by features of natural outdoor environments (e.g., size, type, biodiversity, and quality), nature contact (e.g., visual, and auditory), and interaction (e.g., time spent, and visiting frequency) (Bratman et al., 2019; Frumkin et al., 2017). The detailed characteristics and temporal profiles of nature exposure are needed for better designs of future greening interventions. Third, although our study established statistical associations between availability of greenness and COVID-19 outcomes, it does not imply cause-and-effect relationships. To confirm causality, future research could employ methods of causal inference (e.g., difference-in-difference method, and structural equation model). Fourth, our study didn't consider different variants of COVID-19 (e.g., Delta, and Omicron) as this information was not recorded in the COVID-19 case report form. Given the limitations of this research, our findings should be interpreted as working hypotheses from which to design future targeted nature-based interventions and greening policies that promote public health.

5. Conclusions

Overall, our findings indicate that availability of greenness is associated with the percentage decrease for the COVID-19 infection rate in the US but not with the rates of COVID-19 hospitalizations and deaths. In addition, availability of greenness has limited effects for ameliorating COVID-19 related inequities as greenness availability shows stronger negative associations for men than for women, and for adults than for the elderly. Although our study shows a promising association between greenness and COVID-19 infections, it does not confirm cause-and-effect relationships, nor does it address the underpinning mechanisms that greenness affects COVID-19. Nevertheless, our study provides working hypotheses for the targeted design of nature-based interventions and greening policies to benefit human well-being and reduce health inequity.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104704.

References

Anderson, T. J., Saman, D. M., Lipsky, M. S., & Lutfiyya, M. N. (2015). A cross-sectional study on health differences between rural and non-rural US counties using the County Health Rankings. *BMC Health Services Research, 15*(1), 1–8.
Astell-Burt, T., & Feng, X. (2021). Time for 'green'during COVID-19? Inequities in green and blue space access, visitation and felt benefits. *International Journal of Environmental Research and Public Health, 18*(5), 2757.
Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociocchi, W. (2020). Economic and social consequences of human mobility restrictions under COVID-19, *Proceedings of the National Academy of Sciences* **117**(27)**:**15530-15535.
Bratman, G. N., Anderson, C. B., Berman, M. G., Cochran, B., De Vries, S., Flanders, J., … Hartig, T. (2019). Nature and mental health: An ecosystem service perspective. *Science Advances, 5*(7). eaax0903.
Cao, Y., Hiyoshi, A., & Montgomery, S. (2020). COVID-19 case-fatality rate and demographic and socioeconomic influencers: Worldwide spatial regression analysis based on country-level data. *BMJ open, 10*(11), e043560.
Carrión, D., Colicino, E., Pedretti, N. F., Arfer, K. B., Rush, J., DeFelice, N., & Just, A. C. (2021). Neighborhood-level disparities and subway utilization during the COVID-19 pandemic in New York City. *Nature Communications, 12*(1), 1–10.
Chen, B., Wu, S., Song, Y., Webster, C., Xu, B., & Gong, P. (2022). Contrasting inequality in human exposure to greenspace between cities of Global North and Global South. *Nature Communications, 13*(1), 1–9.
Cohen, J. (1992). Statistical power analysis. *Current Directions in Psychological Science, 1*(3), 98–101.
Dadvand, P., Bartoll, X., Basagaña, X., Dalmau-Bueno, A., Martinez, D., Ambros, A., … Borrell, C. (2016). Green spaces and general health: Roles of mental health status, social support, and physical activity. *Environment International, 91*, 161–167.
Frumkin, H., Bratman, G. N., Breslow, S. J., Cochran, B., Kahn, P. H., Jr, Lawler, J. J., … Wolf, K. L. (2017). Nature contact and human health: A research agenda. *Environmental Health Perspectives, 125*(7), Article 075001.
Fuertes, E., Markevych, I., von Berg, A., Bauer, C.-P., Berdel, D., Koletzko, S., … Heinrich, J. (2014). Greenness and allergies: Evidence of differential associations in two areas in Germany. *J Epidemiol Community Health, 68*(8), 787–790.
Geary, R. S., Wheeler, B., Lovell, R., Jepson, R., Hunter, R., & Rodgers, S. (2021). A call to action: Improving urban green spaces to reduce health inequalities exacerbated by COVID-19. *Preventive Medicine, 145*, Article 106425.
Gerrish, E., & Watkins, S. L. (2018). The relationship between urban forests and income: A meta-analysis. *Landscape and Urban Planning, 170*, 293–308.
Harlan, S. L., & Ruddell, D. M. (2011). Climate change and health in cities: Impacts of heat and air pollution and potential co-benefits from mitigation and adaptation. *Current opinion in environmental sustainability, 3*(3), 126–134.
Huang, B., Huang, Z., Chen, C., Lin, J., Tam, T., Hong, Y., & Pei, S. (2022). Social vulnerability amplifies the disparate impact of mobility on COVID-19 transmissibility across the United States. *Humanities and Social Sciences Communications, 9*(1), 1–13.
Huang, J., Kwan, M.-P., Kan, Z., Wong, M. S., Kwok, C. Y. T., & Yu, X. (2020). Investigating the relationship between the built environment and relative risk of COVID-19 in Hong Kong. *ISPRS International Journal of Geo-Information, 9*(11), 624.
Hughey, S. M., Walsemann, K. M., Child, S., Powers, A., Reed, J. A., & Kaczynski, A. T. (2016). Using an environmental justice approach to examine the relationships between park availability and quality indicators, neighborhood disadvantage, and racial/ethnic composition. *Landscape and Urban Planning, 148*, 159–169.
Ingram, D. D., & Franco, S. J. (2012). NCHS urban-rural classification scheme for counties, *Vital and health statistics. Series 2. Data evaluation and methods research, 154*, 1–65.

Ingram, D. D., Franco, S. J. (2014). 2013 NCHS urban-rural classification scheme for counties, *National Center for Health Statistics*: https://www.cdc.gov/nchs/data_access/urban_rural.htm.
James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports, 2*(2), 131–142.
Jennings, V., & Gaither, C. J. (2015). Approaching environmental health disparities and green spaces: An ecosystem services perspective. *International journal of environmental research and public health, 12*(2), 1952–1968.
Jiang, B., Yang, Y., Chen, L., Liu, X., Wu, X., Chen, B., Webster, C., Sullivan, W. C., Wang, J., Lu, Y. (2021). Green spaces, especially forest, linked to lower SARS-CoV-2 infection rates: A one-year nationwide study, *medRxiv*.
Jin, J., Agarwala, N., Kundu, P., Harvey, B., Zhang, Y., Wallace, E., & Chatterjee, N. (2021). Individual and community-level risk for COVID-19 mortality in the United States. *Nature Medicine, 27*(2), 264–269.
Kleinschroth, F., & Kowarik, I. (2020). COVID-19 crisis demonstrates the urgent need for urban greenspaces. *Frontiers in Ecology and the Environment, 18*(6), 318.
Klompmaker, J. O., Hart, J. E., Holland, I., Sabath, M. B., Wu, X., Laden, F., … James, P. (2021). County-level exposures to greenness and associations with COVID-19 incidence and mortality in the United States. *Environmental Research, 199*, Article 111331.
Kraemer, H. C., & Blasey, C. (2015). How many subjects?: Statistical power analysis in research. *Sage*. Publications.
Kuo, F. E., & Sullivan, W. C. (2001). Environment and crime in the inner city: Does vegetation reduce crime? *Environment and Behavior, 33*(3), 343–367.
Kuo, M. (2015). How might contact with nature promote human health? Promising mechanisms and a possible central pathway. *Frontiers in Psychology, 6*, 1093.
Labib, S., Browning, M. H., Rigolon, A., Helbich, M., & James, P. (2021). Nature's contributions in coping with a pandemic in the 21st century: A narrative review of evidence during COVID-19. *EcoEvoRxiv Preprints:Https://*. https://doi.org/10.32942/osf.io/j2pa8
Lee, W., Kim, H., Choi, H. M., Heo, S., Fong, K. C., Yang, J., … Bell, M. L. (2021). Urban environments and COVID-19 in three Eastern states of the United States. *Science of The Total Environment, 779*, Article 146334.
Lin, J. (2020). Developing a composite indicator to prioritize tree planting and protection locations. *Science of the Total Environment, 717*, Article 137269.
Lin, J., Kroll, C. N., Nowak, D. J., & Greenfield, E. J. (2019). A review of urban forest modeling: Implications for management and future research. *Urban Forestry & Urban Greening, 43*, Article 126366.
Lin, J., Wang, Q., & Huang, B. (2021a). Street trees and crime: What characteristics of trees and streetscapes matter. *Urban Forestry & Urban Greening, 65*, 127366.
Lin, J., Wang, Q., & Li, X. (2021b). Socioeconomic and spatial inequalities of street tree abundance, species diversity, and size structure in New York City. *Landscape and Urban Planning, 206*, Article 103992.
Lu, Y., Chen, L., Liu, X., Yang, Y., Sullivan, W. C., Xu, W., … Jiang, B. (2021). Green spaces mitigate racial disparity of health: A higher ratio of green spaces indicates a lower racial disparity in SARS-CoV-2 infection rates in the USA. *Environment International, 152*, Article 106465.
Ma, Y., Pei, S., Shaman, J., Dubrow, R., & Chen, K. (2021). Role of meteorological factors in the transmission of SARS-CoV-2 in the United States. *Nature Communications, 12*(1), 1–9.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., … Nieuwenhuijsen, M. J. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental research, 158*, 301–317.
Marselle, M. R., Hartig, T., Cox, D. T., De Bell, S., Knapp, S., Lindley, S., … Cook, P. A. (2021). Pathways linking biodiversity to human health: A conceptual framework. *Environment International, 150*, Article 106420.
Matthews, K. A., Croft, J. B., Liu, Y., Lu, H., Kanny, D., Wheaton, A. G., … Holt, J. B. (2017). Health-related behaviors by urban-rural county classification—United States, 2013. *MMWR Surveillance Summaries, 66*(5), 1.
Meyers, L. S., Gamst, G., & Guarino, A. J. (2016). Applied multivariate research: Design and interpretation. *Sage*. publications.
Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *The Lancet, 372*(9650), 1655–1660.
Morello-Frosch, R., & Lopez, R. (2006). The riskscape and the color line: Examining the role of segregation in environmental health disparities. *Environmental research, 102*(2), 181–196.
Nesbitt, L., Meitner, M. J., Girling, C., Sheppard, S. R., & Lu, Y. (2019). Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 US cities. *Landscape and Urban Planning, 181*, 51–79.
Nguyen, Q. C., Huang, Y., Kumar, A., Duan, H., Keralis, J. M., Dwivedi, P., … Javanmardi, M. (2020). Using 164 million Google Street View images to derive built environment predictors of COVID-19 cases. *International Journal of Environmental Research and Public Health, 17*(17), 6359.
Pan, J., Bardhan, R., & Jin, Y. (2021). Spatial distributive effects of public green space and COVID-19 infection in London. *Urban Forestry & Urban Greening, 62*, Article 127182.
Pearsall, H., & Pierce, J. (2010). Urban sustainability and environmental justice: Evaluating the linkages in public planning/policy discourse. *Local Environment, 15*(6), 569–580.
Russette, H., Graham, J., Holden, Z., Semmens, E. O., Williams, E., & Landguth, E. L. (2021). Greenspace exposure and COVID-19 mortality in the United States: January–July 2020. *Environmental Research, 198*, Article 111195.
Schaeffer, K. (2019). The most common age among whites in US is 58—more than double that of racial and ethnic minorities, *Pew Research Center*.
Sera, F., Armstrong, B., Abbott, S., Meakin, S., O'Reilly, K., von Borries, R., … Pascal, M. (2021). A cross-sectional analysis of meteorological factors and SARS-CoV-2 transmission in 409 cities across 26 countries. *Nature Communications, 12*(1), 1–11.
Shakor, A., Su'ad, A., Pahrol, M. A., Mazeli, M. I. (2020). Effects of population weighting on PM10 concentration estimation, *Journal of Environmental and Public Health* **2020**.
Spotswood, E. N., Benjamin, M., Stoneburner, L., Wheeler, M. M., Beller, E. E., Balk, D., … McDonald, R. I. (2021). Nature inequity and higher COVID-19 case rates in less-green neighbourhoods in the United States. *Nature*. Sustainability:1–7.
Sreetheran, M., & Van Den Bosch, C. C. K. (2014). A socio-ecological exploration of fear of crime in urban green spaces–A systematic review. *Urban Forestry & Urban Greening, 13*(1), 1–18.
Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., & Marshall, J. D. (2021). PM2. 5 polluters disproportionately and systemically affect people of color in the United States. *Science Advances, 7*(18). eabf4491.
Venter, Z. S., Shackleton, C., Faull, A., Lancaster, L., Breetzke, G., & Edelstein, I. (2022). Is green space associated with reduced crime? A national-scale study from the Global South. *Science of the total environment, 825*, Article 154005.
Wen, Q., Yang, J., & Luo, T. (2020). First case of covid-19 in the United States. *N. Engl. J. Med, 382*, e53.
Williams, D. R., Priest, N., Anderson, N. (2019). Understanding associations between race, socioeconomic status, and health: patterns and prospects, in: *The Social Medicine Reader, Volume II, Third Edition*, Duke University Press, pp. 258-267.
Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and urban planning, 125*, 234–244.
Xue, T., Zhu, T., Zheng, Y., & Zhang, Q. (2019). Declines in mental health associated with air pollution and temperature variability in China. *Nature Communications, 10*(1), 1–8.
You, Y., & Pan, S. (2020). Urban vegetation slows down the spread of coronavirus disease (COVID-19) in the United States. *Geophysical Research Letters, 47*(18). e2020GL089286.
Zhang, L., Ma, Z., & Guo, L. (2009). An evaluation of spatial autocorrelation and heterogeneity in the residuals of six regression models. *Forest Science, 55*(6), 533–548.
Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R*. Springer.