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Racial disparities in environmental exposures and SARS-CoV-2 infection rates: A detailed population-weighted analysis

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ABSTRACT

The COVID-19 pandemic has cast a spotlight on the intersection of socio-economic, demographic, and environmental factors with public health, particularly in the context of SARS-CoV-2 infection rates. A gap remains in understanding how racial disparities in environmental exposure correlate with racial disparities in infection rates. This study bridges this gap by analyzing infection data for black and white populations across 1,416 counties in the contiguous United States, utilizing high-resolution land cover data and racial population maps to assess environmental exposure disparities. We found significant connections between racial disparities in environmental exposure and SARS-CoV-2 infection rates, even after accounting for population density, socio-economic status, and demographic factors. Disparities among black and white population's access to green spaces, such as non-park forests and pasture/hay areas, as well as to developed areas of varying intensities, closely mirror racial disparities in infection rates. Crucially, we found that smaller differences in environmental exposure between races are associated with smaller differences in infection rates. This relationship is most pronounced within a 400-meter radius, underscoring the critical role of proximity in the design of urban and landscape environments to promote public health equity.

1. Introduction

1.1. Background

Racial disparities in health outcomes are complex and urgent issues globally (Braveman et al., 2011). Research has shown that socio-economic and demographic disparities can lead to varied environmental exposures, impacting health outcomes (Benita et al., 2022; Song et al., 2021; World Health Organization, 2010). A growing body of evidence suggests a link between environmental disparities in different landscapes and urban settings and racial disparities in SARS-CoV-2 infection rates (e.g., Jamshidi et al., 2020; Lu et al., 2021a; Spotswood et al., 2021; Zhang & Schwartz, 2020). These studies, however, typically miss key factors, such as variations in green space access across racial groups and the characteristics of these green spaces (e.g., Spotswood et al., 2021). Additionally, limitations like small sample sizes (e.g., Lu et al., 2021a) leave significant gaps in our understanding. The study presented below examines into the relationship between racial disparities in access to green and developed spaces and their correlation with SARS-CoV-2 infection rates, aiming to guide effective resource allocation and enhance equitable access to supportive environments, thereby reducing racial health disparities.

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We define "disparity" as a difference, without implying the nature or implications of that difference (Webster, 2005). In this study, racial disparity refers to differences among racial groups in environmental exposure or health and wellbeing indicators.

Previous research on environmental variables and SARS-CoV-2 infection rates primarily focused on four relationships:

- Green space exposure and SARS-CoV-2 infection rates.
- Racial differences in green space exposure and SARS-CoV-2 infection rates.
- Exposure to developed spaces and SARS-CoV-2 infection rates.
- Racial disparities in exposure to developed spaces and SARS-CoV-2 infection rates.

We explore these studies and describe the gaps in our knowledge in the sections that follow.

1.2. Green space exposure and potential impacts on SARS-CoV-2 infection

Green space exposure, encompassing both passive and active interactions with various green spaces, has been linked to SARS-CoV-2 infection rates. Studies generally suggest that increased time in green spaces can lower infection risk. For example, a 1 % increase in tree canopy at the county level correlated with a significant decrease in infections, highlighting green spaces' protective benefits (Klompmaker et al., 2021). Areas with more green spaces experienced slower COVID-19 transmission (Alidadi & Sharifi, 2022) and fewer infections and related deaths (Jiang et al., 2022; Yang et al., 2022). Still, densely populated cities with abundant public landscapes saw more cases in the pandemic's early days, possibly due to increased social interactions in these spaces (Lu et al., 2021b). Another study emphasized the role of natural landscapes in mitigating future pandemic risks and promoting public health (Li & Managi, 2023).

1.3. Racial disparities in green space exposure and SARS-CoV-2 infection

Few studies directly link racial differences in green space access to SARS-CoV-2 infection rates. Indications are that larger racial gaps in green space access may lead to greater infection disparities (e.g., Lu et al., 2021a; Spotswood et al., 2021). These studies, however, have limitations. For instance, one study found that in the 135 most urbanized U.S. counties, those with more green spaces had smaller racial disparities in infection rates (Lu et al., 2021a). But this study did not include less urban areas or consider the spatial distribution of racial groups and green spaces. Another study suggested that lower racial disparity in green space access correlated with fewer COVID-19 cases (Spotswood et al., 2021), but it used the Normalized Difference Vegetation Index (NDVI) for measuring greenness, which lacks specificity in differentiating various types of green space. These studies often fail to consider the precise locations of green spaces and racial groups, leading to potential inaccuracies.

1.4. Exposure to developed spaces and SARS-CoV-2 infection rates

Developed spaces, combining constructed materials and vegetation, vary in non-natural surface area: low (20–49 %), moderate (50–79 %), or high (80–100 %) development intensity. Research shows that urban development intensity can differentially impact public health (e.g., Kashem et al., 2021; McMichael, 2000; Son et al., 2020). Urbanized areas can negatively affect mental and physical health due to limited green space access (Das et al., 2008; Jiang et al., 2022; Luo & Jiang, 2022; Venkatramana & Reddy, 2002). Conversely, they can offer benefits like improved social security and vitality (Jauho & Helén, 2022; Mouratidis & Poortinga, 2020). Understanding the interplay between green spaces and urban areas, particularly their combined effect on SARS-CoV-2 infection rates, is crucial (Jiang et al., 2022; Paköz & Işık, 2022).

Studies suggest that denser urban areas correlate with higher infection and mortality rates (e.g., Jamshidi et al., 2020; Lin et al., 2020; Zhang & Schwartz, 2020). Less dense areas may offer lower risk due to open spaces facilitating social distancing and reduced airborne virus particles (Jiang et al., 2022; Lin et al., 2020; Wang et al., 2021). The complexity and variability of developed areas in the U.S. is not fully captured by simple linear analyses that is typical of these previous studies.

1.5. Racial disparities in developed space exposure and SARS-CoV-2 infection rates

We know little about the link between racial disparities in developed space exposure and SARS-CoV-2 infection rates. One study focused on highly urbanized U.S. counties but excluded three developed space measures due to data overlap (Lu et al., 2021a). This study also did not consider a range of urban development exposures. Another study used NDVI to estimate urban development intensity (Spotswood et al., 2021), but NDVI provides only a rough measure, which begs for more precise methods in an effort to deepen our understanding. Neither study fully accounted for the spatial distribution of racial groups and varying development intensities, potentially leading to an ecological fallacy.

1.6. Gaps in our knowledge

Our understanding of the relationship between racial disparities in green and developed space exposure and SARS-CoV-2 infection rates has five key gaps.

First, existing research has often overlooked the geographical distribution of racial groups. This neglect complicates our ability to gauge the exposure to nearby landscapes and urban settings among racial groups, making findings susceptible to an ecological fallacy.

Second, many cross-sectional studies have not used within-county racial comparisons. By focusing on within-county disparities, we can reduce the risk of ecological fallacy, as this approach reduces biases arising from distinct conditions across different spatial locations (Lu et al., 2021a).

Third, previous studies have employed NDVI or overall greenness to measure green space exposure. This approach cannot distinguish between different types of green spaces and their respective outcomes.

Fourth, comprehensive measurements of urban exposure are lacking in existing studies, which creates a knowledge void regarding the relationship between levels of urban development and racial disparities in SARS-CoV-2 infection rates.

Finally, most research to date related to these questions focuses on highly urbanized areas or smaller, specific regions, limiting the generalizability of their findings on a broader, national scale, especially in countries with a great variety in urban densities.

1.7. Research objectives

Our study, spanning 12 months and using high-resolution land cover and racial population maps, seeks to answer five key questions:

- Were there significant differences in SARS-CoV-2 infection rates between black and white individuals?
- To what extent do black and white individuals differ in the availability of green and developed spaces?
- Were green and developed space availability statistically linked to infection rates among black and white individuals?
- How strongly were racial differences in green and developed space availability related to racial disparities in SARS-CoV-2 infection rates?

- To what extent did the association between racial disparities in green and developed space availability and SARS-CoV-2 infection rates vary with different buffer distances?

2. Methods

Our study adopted a within-county research design, analyzing 1416 counties across the contiguous United States. We collected data on COVID-19 cases from January 1, 2020, to December 31, 2020. The focus was on racial disparities in environmental exposures and infection rates between black and white populations within the same counties. Our methodology included defining study areas, determining SARS-CoV-2 infection rates, measuring green and developed space exposures, understanding socio-economic and demographic factors, and conducting statistical analysis.

2.1. Selection of study areas

Counties, as principal administrative divisions in the US, were our basic analytical units. We accessed data on infection cases, including race and ethnicity details, for 3108 counties from the US Centers for Disease Control and Prevention (CDC, 2021). After excluding 1691 counties due to missing racial data for black and/or white groups, and La Salle County in Texas due to data inconsistencies, we finalized a sample of 1416 counties.

Of these, 1223 counties (86.4 %) had a black population of at least 2 %. The remaining counties were excluded primarily due to insignificant black populations. Each selected county had a white population exceeding 6 %.

2.2. Measuring SARS-CoV-2 infection rates

We calculated infection rates among black and white populations using 2019 census data (US Census Bureau, 2020). The racial gap in infection rates was assessed by comparing rates between black and white individuals within the same county.

2.3. Mapping land cover and racial populations

2.3.1. Classification of green and developed spaces

Using the 2019 National Land Cover Database (NLCD), we identified two primary land cover categories: green spaces and developed spaces. Green spaces included developed open spaces, various forest types, grasslands, and pasture/haylands. Developed spaces were categorized by development intensity:

a) Low development: Predominantly vegetative areas with 20–49 % impervious surfaces
b) Medium development: Areas mainly containing single-family homes with 50–79 % impervious surfaces
c) High development: Highly trafficked areas with 80–100 % impervious surfaces.

2.3.2. High-resolution racial population mapping

In our study, mapping of black and white populations across the United States was accomplished with high-resolution racial data provided by the SocScape (Social Landscape) initiative. SocScape supplies resources that facilitate a detailed visualization and analysis of residential segregation and racial diversity patterns across the contiguous US and its metropolitan areas. This platform is adept at offering insights into the spatial distribution of racial groups.

A key feature of the SocScape resource is its detailed 30 m grid representations, which encompass seven distinct racial or ethnic subgroups. This granularity allows for an accurate and detailed understanding of the racial composition at fine-grained level. We focused exclusively on the grid data pertaining to non-Hispanic whites and non-Hispanic blacks. This selection was driven by our research objective to examine the disparities between these two groups.

One of the innovative aspects of SocScape's methodology is its use of dasymetric modeling in the creation of these 30 m grids, based on racial population with one dot per person (see Fig. 1 for an example). Dasymetric modeling enhances the accuracy of demographic data representation by incorporating additional geographic information into the population distribution models. This approach contrasts with, and offers improvements over, the more traditional methods of aggregating population data, such as those based on Census tracts or blocks. The superiority of this method in representing population data more accurately has been well-documented in the literature (Dmowska & Stepinski, 2019; Dmowska et al., 2017).

2.3.3. Assessment of green space availability

Our assessment of green space availability is a critical component of this study, as it provides insights into the potential association between green spaces and racial disparities in COVID-19 infection rates. This assessment was conducted through a two-step process involving the classification of green spaces and the calculation of population-weighted green space exposure.

2.3.3.1. Green space classification and park boundaries. Initially, we classified green spaces using a 30 m resolution, which allowed us to evaluate four distinct types of green spaces that are primarily composed of natural elements. This classification distinguished between different types of green spaces, such as developed open spaces and forests. We further refined this classification by considering park boundaries, which enabled us to categorize these spaces into two groups: those located within park boundaries and those outside. This distinction is significant as it recognizes the varying levels of accessibility and potential health benefits associated with green spaces that are formally designated as parks (ESRI, 2021).

2.3.3.2. Population-Weighted green space exposure calculation. To quantify the exposure of black and white populations to these green spaces, we calculated a population-weighted measure of green space availability. This measure was adjusted for population density within predetermined buffer distances in each county, thereby emphasizing the importance of green spaces that are in closer proximity to denser population areas. The rationale behind this approach is that green spaces near more populated areas are likely to have a greater impact on public health due to their increased accessibility and use (Chen et al., 2018a, b; Chen et al., 2022; Song et al., 2021; Yang et al., 2022).

The calculation was performed using Google Earth Engine (GEE) in conjunction with the National Land Cover Database (NLCD) 2019 dataset. The congruence of the 30 m spatial resolution of the 2019 Landsat imagery from NLCD and the racial map in GEE was instrumental in facilitating precise computations of green space exposure for various buffer distances within each county.

The formula for calculating race population-weighted green space exposure within a specified buffer distance (d) for a given county is expressed as:

$$GE^d = \frac{\sum_{i=1}^{N} P_i \times G_i^d}{\sum_{i=1}^{N} P_i}$$

In this formula, P_i represents the population count (either black or white) in the i th grid. G_i^d denotes the green space within a buffer of d meters around the i th grid cell, and N is the total number of grid cells within the county. The result, GE^d provides an estimate of the green space availability for the county's population (Fig. 2).

By examining a range of buffer sizes, from 100 m up to 5 kms (which is considered the maximum practical walking distance in the U.S., as per Yang & Diez-Roux, 2012), we aimed to explore the relationship between the proximity to green spaces and the disparities in infection rates

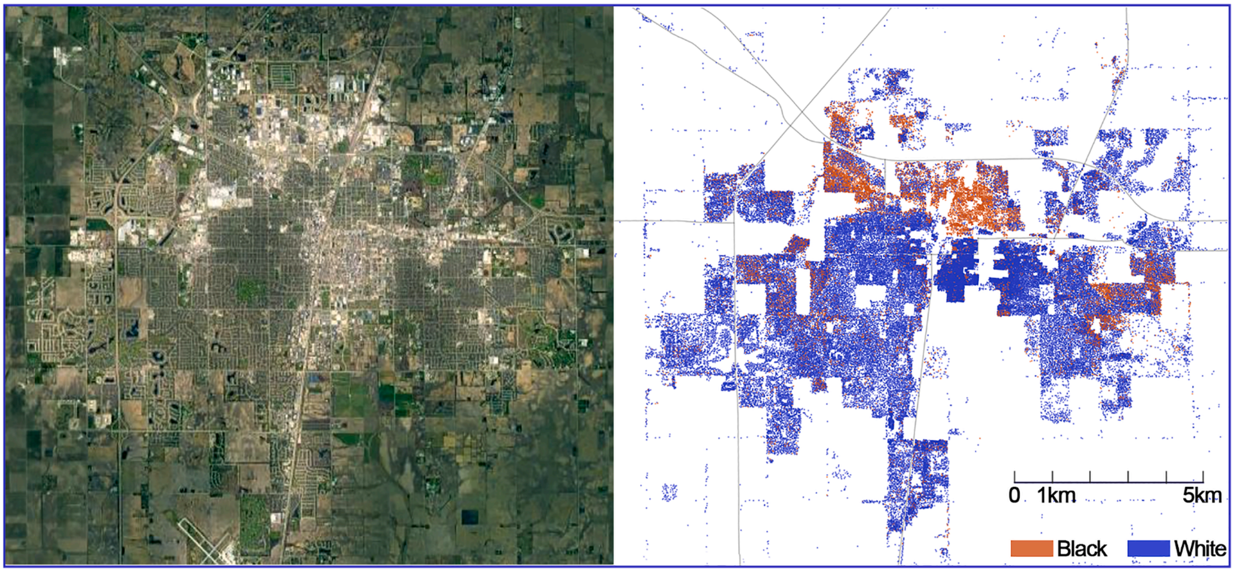

Fig. 1. Left: Google Earth image of an ordinary county with urban, suburban and rural areas, Champaign-Urbana, Illinois, USA; Right: The racial dot map of the same region showing housing location of black and white individuals (one dot per person).

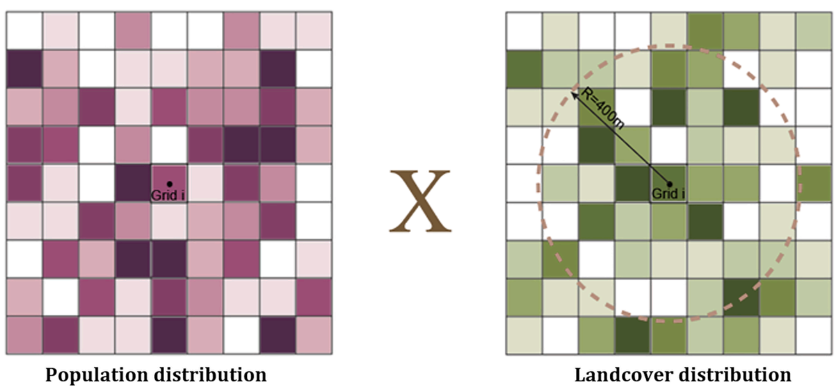

Fig. 2. Methodological diagram of population-weighted exposure to landcover within a given buffer (i.e., 400 m buffer in this example). Population-weighted exposure to landcover considers the relative spatial distribution of population and landcover, and gives a higher weighting to landcover close to densely populated area (see Eq. 1). The buffer distance is calculated from the center of the grid, and a grid is included in the buffer zone if the center point of the grid falls inside the buffer zone (the dashed line circle).

between black and white populations. The disparities in green space availability were then used as predictor variables in a generalized linear mixed model to investigate their potential influence on the observed racial disparities in infection rates.

2.3.4. Assessment of developed space exposure

In parallel with green spaces, we also assessed exposure to developed spaces, which are critical in understanding the environmental context of each county. Utilizing the NLCD 2019 data, we categorized developed spaces into three tiers based on development intensity: low, medium, and high. This categorization allowed us to systematically evaluate the impact of different levels of urban development on population health.

The methodology for assessing exposure to developed spaces mirrored that of the green space assessment. We applied the same buffer distances, ranging from 100 m to 5 kms, to assess the differential exposure experienced by black and white populations within these developed areas. This comprehensive approach ensures that our analysis captures the full spectrum of environmental exposures that may contribute to racial disparities in COVID-19 infection rates.

2.4. Adjustments for socio-economic and demographic variables

Recognizing the significant influence of socio-economic and demographic factors on the risk of SARS-CoV-2 infection and the associated racial disparities, our study incorporates a comprehensive adjustment process for these variables. This step acknowledges the complex interplay between environmental exposures and socio-economic conditions, which can have profound impacts on health outcomes.

Prior research has consistently highlighted the importance of socio-economic and demographic characteristics in shaping health disparities (Abedi et al., 2020; Figueroa et al., 2020). Thus, our analysis began with a thorough examination of potential collinearity between environmental exposure factors and population density—a common concern in environmental health research. The correlational analysis reveals that there are moderate associations between population-weighted environmental exposure and population density, which suggest they are correlated but they do not have a significant multicollinearity problem (Fig. 3). This finding validates our approach of greenspace and developed exposure in accounting for population density and supports the independence of environmental exposure factors in our models,

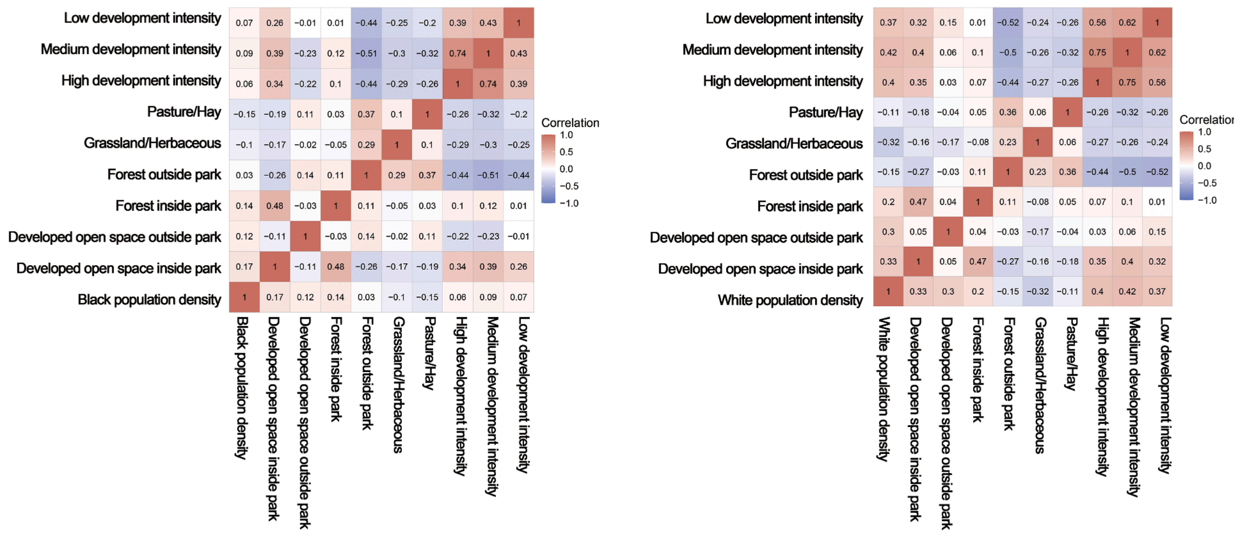

Fig. 3. Correlation analysis to investigate the potential relationship between population density among Black and White individuals and their corresponding exposure to green and developed spaces (exposure to green and developed spaces were calculated by the Population-Weighted method).

allowing for a more accurate interpretation of their effects.

Next, we adjusted our analysis for a range of socio-economic and demographic variables that could confound the relationship between environmental exposures and infection rates. These adjustments were made to isolate the specific impact of green and developed space exposures on the observed racial disparities in infection rates. The variables considered include, but are not limited to, income levels, educational attainment, employment status, and age distribution, which have been shown to correlate with health outcomes across different racial groups (Dmowska et al., 2017; Spotswood et al., 2021).

The descriptive statistics for these socio-economic and demographic variables are presented in Table 1, offering a snapshot of the conditions within the 1416 counties included in our study. For a more detailed breakdown of these variables and their distribution across the study areas, readers are directed to Appendix Table A1(b). This level of detail ensures transparency and allows for a nuanced understanding of the factors at play in our analysis.

2.5. Overview of statistical framework

The primary architecture of our statistical analysis is illustrated in Fig. 4, which encompasses five key components. These components directly align with the research objectives described in Section 1.7.

In the following paragraphs, we describe the statistical methodologies employed in our investigation.

Comparing Racial Disparities: To identify significant differences in SARS-CoV-2 infection rates and levels of exposure to green and developed spaces between black and white populations within the same counties, we applied the Wilcoxon signed-rank test. This non-parametric test is particularly suited for paired data, allowing us to make direct comparisons within counties.

Regression Analysis: We utilized negative binomial regression to explore the association between exposure to green and developed spaces and SARS-CoV-2 infection rates. In this context, infection rates among black and white populations were analyzed as dependent variables. We incorporated socio-economic and demographic characteristics as covariates. Additionally, to account for data dependency within states, we introduced a random intercept for each state.

Mixed Model Examination: Our analysis employed generalized linear mixed models, which allowed us to examine the relationship between disparities in exposure to green and developed spaces and racial disparities in infection rates. These models treated disparities in exposure to spaces as independent variables and the differences in infection rates between races as dependent variables. We controlled for socio-economic and demographic differences between racial groups as covariates and included a random intercept for states to address correlations between counties within the same state.

Buffer Distance: A fixed buffer distance of 400 m was consistently used across all models to calculate population-weighted exposures. This distance is reflective of typical walking distances in the U.S. (Yang & Diez-Roux, 2012) and aligns with the World Health Organization's recommendations for physical activity (2016).

Buffer Distance Variability: We examined the relationship between racial disparities in infection rates and proximity to green spaces at various buffer distances, ranging from 100 m to 1800 m, increasing incrementally by 200 m, and from 2 kms to 5 kms, using 500-meter intervals. This analysis aimed to understand how the influence of green space exposure on infection rates might change over different spatial extents.

Addressing Spatial Autocorrelation: To mitigate the potential bias from spatial autocorrelation, we constructed simultaneous autoregressive models (SAR). These models were used to confirm and adjust for spatial autocorrelation within our data. We employed the queen criterion to establish a neighbors matrix and utilized the Akaike Information Criterion (AIC) for model selection, comparing three possible structures: a spatial error model, a spatial lag model, and a mixed or Durbin model, each assuming spatial dependence in different components of the model.

Software and Model Refinement: Data processing and analysis were conducted using R software, version 4.1.1, employing functions 'glmer.nb' and 'lmer' for model fitting. We addressed multicollinearity by excluding variables with a variance inflation factor (VIF) of 4 or greater. The outputs reported include model coefficient estimates, standard errors, degrees of freedom, t-values, and p-values for these estimates.

Sensitivity Analysis: To assess the robustness of our findings, we performed a sensitivity analysis using a spatially based random sampling method. The U.S. was divided into nine divisions, and a sampling threshold was applied to generate five distinct sample sets. Analysis of these sets revealed consistent results, reinforcing the reliability of our primary dataset comprising 1416 counties. Detailed results from this sensitivity analysis are presented in Appendix C.

Table 1
Descriptive statistics of the socioeconomic and demographic variables of 1320 counties (96 counties without the information).

Variables	Min	Max	Mean	SD
Population density of all racial groups	2.5	19,625.8	200.9	835.1
Population density of non-Hispanic Black residents	0.03	3556.4	37.1	183.7
Median household income of Black residents	2499	250,001	39,674	17,874
Median age of Black residents	15.7	57.4	34.5	5.8
Percentage of non-Hispanic Black residents	3.0	87.2	17.3	17.0
Percentage of the Black residents in labor force	1.0	94.4	63.7	14.2
Percentage of the Black residents in poverty	0	73.0	26.5	11.1
Black attained less than high school diploma	0	51.9	17.6	8.1
Black of high school graduate or equivalency	0	67.3	35.1	9.5
Black of attained some college or associate's degree	0	83.9	30.9	8.1
Black of attained bachelor's degree or higher	0	80.0	16.4	10.2
Percentage of Black residents less than 18 years	0	55.7	23.7	6.3
Percentage of Black residents 65 years and over	0	36.4	11.3	4.9
Percentage of Black male residents	25.0	98.5	52.4	9.1
Percentage of Black female residents	1.5	75.0	47.6	9.1
Percentage of married Black residents	3.0	58.5	29.9	8.6
Population density of non-Hispanic White residents	0.7	9267.6	106.7	344.0
Median household income of non-Hispanic White residents	26,071	149,087	61,595	17,225
Median age of non-Hispanic White	25.3	69.0	44.0	5.1
Percentage of non-Hispanic White	6.1	96.9	68.5	18.2
Percentage of non-Hispanic White in labor force	39.6	88.9	72.1	7.1
Percentage of non-Hispanic White in poverty	1.0	29.6	11.6	4.5
Non-Hispanic White attained less than high school diploma	0.8	27.4	9.9	4.7
Non-Hispanic White of high school graduate or equivalency	4.3	54.5	31.6	8.0
Non-Hispanic White of attained some college or associate's degree	8.9	45.7	30.8	5.0
Non-Hispanic White of attained bachelor's degree or higher	8.8	86.0	27.8	12.4
Percentage of non-Hispanic Whites less than 18 years	1.7	32.9	19.1	3.0
Percentage of non-Hispanic Whites 65 years and over	8.5	63.8	20.6	4.9
Percentage of non-Hispanic White males	42.9	64.3	49.4	1.7
Percentage of non-Hispanic White females	35.7	57.1	50.6	1.7
Percentage of married non-Hispanic Whites	27.6	74.3	53.2	5.2

3. Results

3.1. Racial disparity in SARS-CoV-2 infection rates

Is there evidence of racial disparities in SARS-CoV-2 infection rates? Yes, and the numbers are striking. As of Dec. 31, 2020, a total of 4370,477 SARS-CoV-2 cases were recorded among black and white people in the 1416 sample counties of the United States (Fig. 5a). The county-level average infection rate for white individuals was 2579 persons per 100,000, in contrast to 3171 per 100,000 for black individuals (Fig. 5b). Thus, the black-white disparity in infection rate was 592 persons per 100,000 population. White individuals exhibited higher infection rates than black individuals in merely 483 of the 1416 sampled counties. A Wilcoxon signed rank test revealed a significant difference in infection rates between black and white individuals, $p < 0.001$.

3.2. Racial disparities in green and developed space exposures

To what extent did black and white individuals differ in the availability of green and developed spaces? Wilcoxon two-sample tests demonstrate that, in comparison to white people, black individuals had significantly lower exposure to various green spaces, including forests, grassland/herbaceous, and pastures/hay lands. Conversely, black individuals experienced significantly greater exposure to highly developed spaces (Figs. 6 and 7). These findings show substantial racial disparities in exposure to green and developed spaces.

3.3. Associations between green and developed space exposure and SARS-CoV-2 infection rates

Were green and developed space availability statistically linked to infection rates among black and white individuals? Significant correlational associations between green and developed space exposures and SARS-CoV-2 infection rates were identified for both racial groups after controlling for social, economic, and demographic covariates (Fig. 8). For black individuals, both forest areas within parks and medium-intensity urban areas yielded significant and negative associations with infection rates ($p < 0.05$). For white individuals, forest areas outside parks revealed significant negative associations with infection rates, while high-intensity urban areas revealed significant and positive associations with infection rates ($p < 0.05$). Detailed information of these associations can be found in Appendix Table A2.

3.4. Association between racial disparities in green and developed space exposures and racial disparity in infection rates

Were racial differences in green and developed space availability significantly related to racial disparities in SARS-CoV-2 infection rates? Yes, a significant negative correlation was revealed by a generalized linear mixed effects model between exposure to forest areas outside parks and pasture lands with racial disparity in SARS-CoV-2 cases. A unit difference in exposure to forest areas outside parks between black and white populations was significantly associated with a 9 % decrease in racial disparity infection rates ($p < 0.001$). We also found a significant association with exposure to pasture/hay settings that resulted in a 5 % decrease in racial disparity infection rates ($p < 0.05$). The difference in exposure to development intensity exerted a mediating effect on SARS-CoV-2 infection rates depending on the levels of intensity. Overall, exposure to developed urban areas with low ($\beta = -0.07$, $p < 0.01$) and medium intensities ($\beta = -0.07$, $p < 0.05$) was significantly associated with low racial disparity of infection rates (Fig. 9, Table 2).

3.5. Changes in the association between racial disparity in green and developed space exposures and SARS-CoV-2 infection rates by buffer distance

To what extent do the associations identified in Section 3.4 persist across a range of distances from an individual's residence? We address this question below, presenting sensitivity analysis results that scrutinize the robustness of these associations at varying distances.

Fig. 10 and Table 3 show the sensitivity analysis for the four significant exposures previously identified. Our analysis reveals that for disparities in exposure to forest areas outside parks, a 400-meter buffer distance emerges as the most predictive of infection rates, with this predictive strength holding up to a 1400-meter radius. In the case of disparities in exposure to pasture and hay areas, the strongest association occurs at a 200-meter buffer distance, with significant predictive power up to 400 m. For disparities in low-intensity developed areas, the 100-meter buffer distance is most indicative of infection rates, maintaining significance up to 600 m. Meanwhile, for moderate-intensity

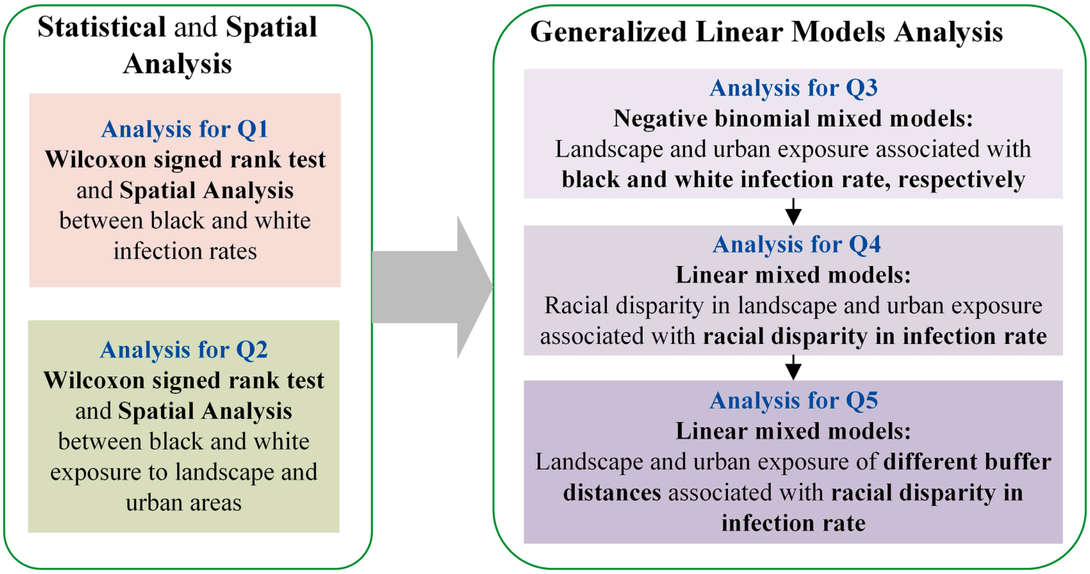

Fig. 4. Analytical Framework Structure: The framework, made up of five integral components, seeks to address the five research inquiries posited.

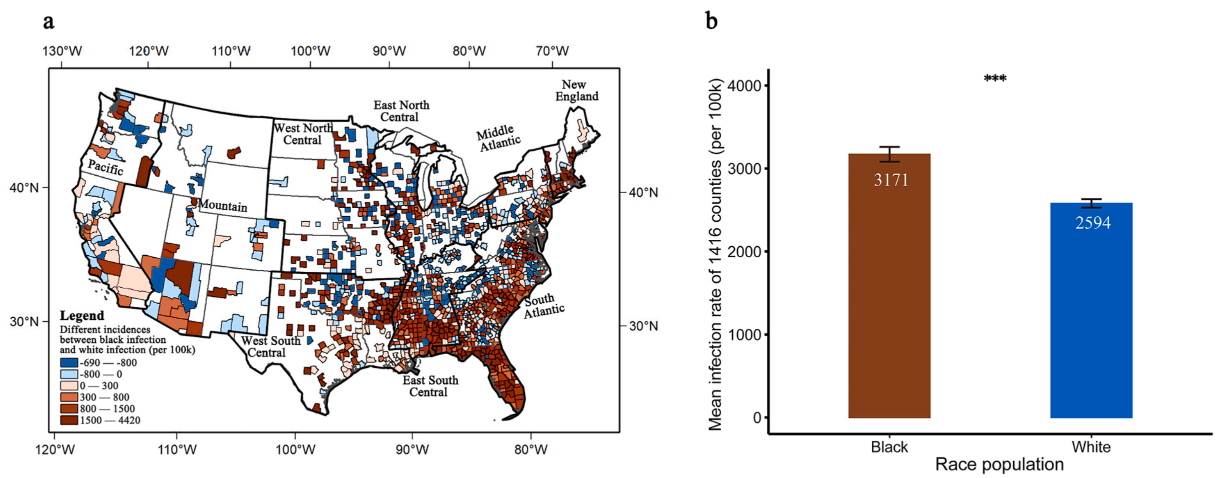

Fig. 5. SARS-CoV-2 infection rate disparities between black and white populations.
a. County-level racial disparities in SARS-CoV-2 infection rates per 100,000 population. Blue indicates higher infection rates among white individuals, and red indicates higher infection rates among black people.
b. Mean SARS-CoV-2 infection rates for black and white populations with significance ($p < 0.001$) verified by a Wilcoxon signed rank test. Error bars indicate standard error of the mean.
References to "black" and "white" populations pertain to non-Hispanic black and non-Hispanic white individuals, respectively.

developed areas, the range of 400 to 1200 m in buffer distance consistently shows significant predictive efficacy.

These findings underscore the significance of the 400-meter buffer distance, as all measures demonstrate substantial associations within this range, corroborating the buffer distance choice for the analyses in prior sections. Note that as the buffer distance extends, the predictive associations between racial disparities in exposure to green and developed spaces and SARS-CoV-2 infection rates begin to wane, with all associations dissipating beyond the 1400-meter mark.

4. Discussion

In this study encompassing 1416 counties across the contiguous United States, we examined the intricate relationships between black and white residents' access to diverse green spaces, the degree of development around their homes, and the SARS-CoV-2 infection rates they experienced over a year. Our investigation yielded three important findings. First, there were pronounced racial disparities in both green and developed space exposures and SARS-CoV-2 infection rates. These disparities were not random but showed consistent patterns across the data. Second, we found that narrowing the racial gap in access to certain environments, such as forests outside parks, agricultural lands, and urban areas with varying development levels, correlated with a decrease in the racial gap in infection rates. Third, the negative correlation between environmental exposure and infection rates was most pronounced at a buffer distance of approximately 400 m, aligning with a distance that is generally considered walkable (Yang & Diez-Roux, 2012).

These findings enrich our understanding of how racial disparities in environmental exposure may influence disparities in SARS-CoV-2 infection rates. They also shed light on potential strategies for addressing public health crises in the future.

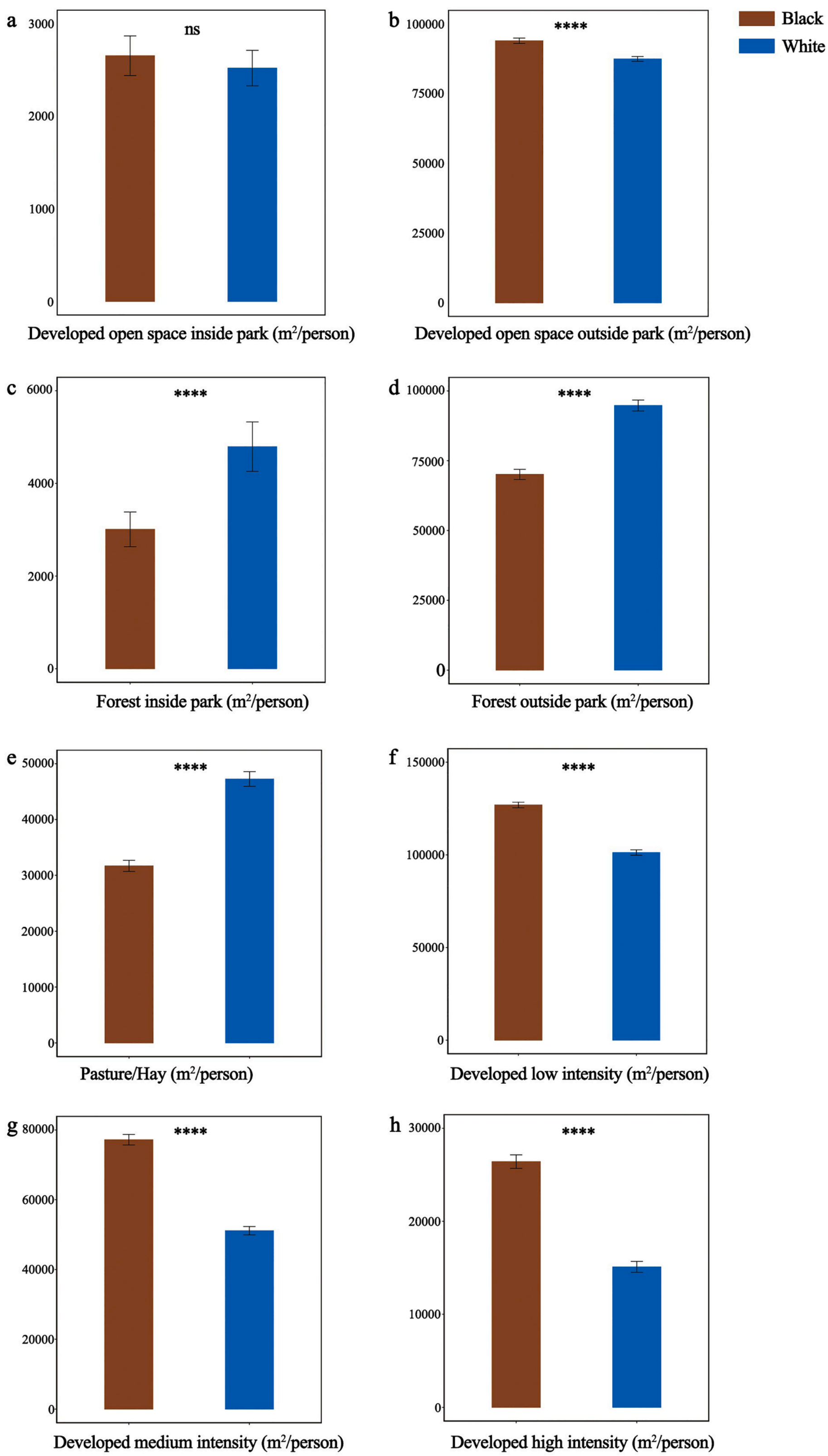

Fig. 6. Green and developed space exposure disparities between black and white populations (within the 400 m buffer distance). The histograms depict mean exposure values for both black and white populations in 1416 counties. Error bars indicate standard error of the mean. '****' represents $p < 0.0001$, 'ns' represents $p \geq 0.1$. References to "black" and "white" populations pertain to non-Hispanic black and non-Hispanic white individuals, respectively.

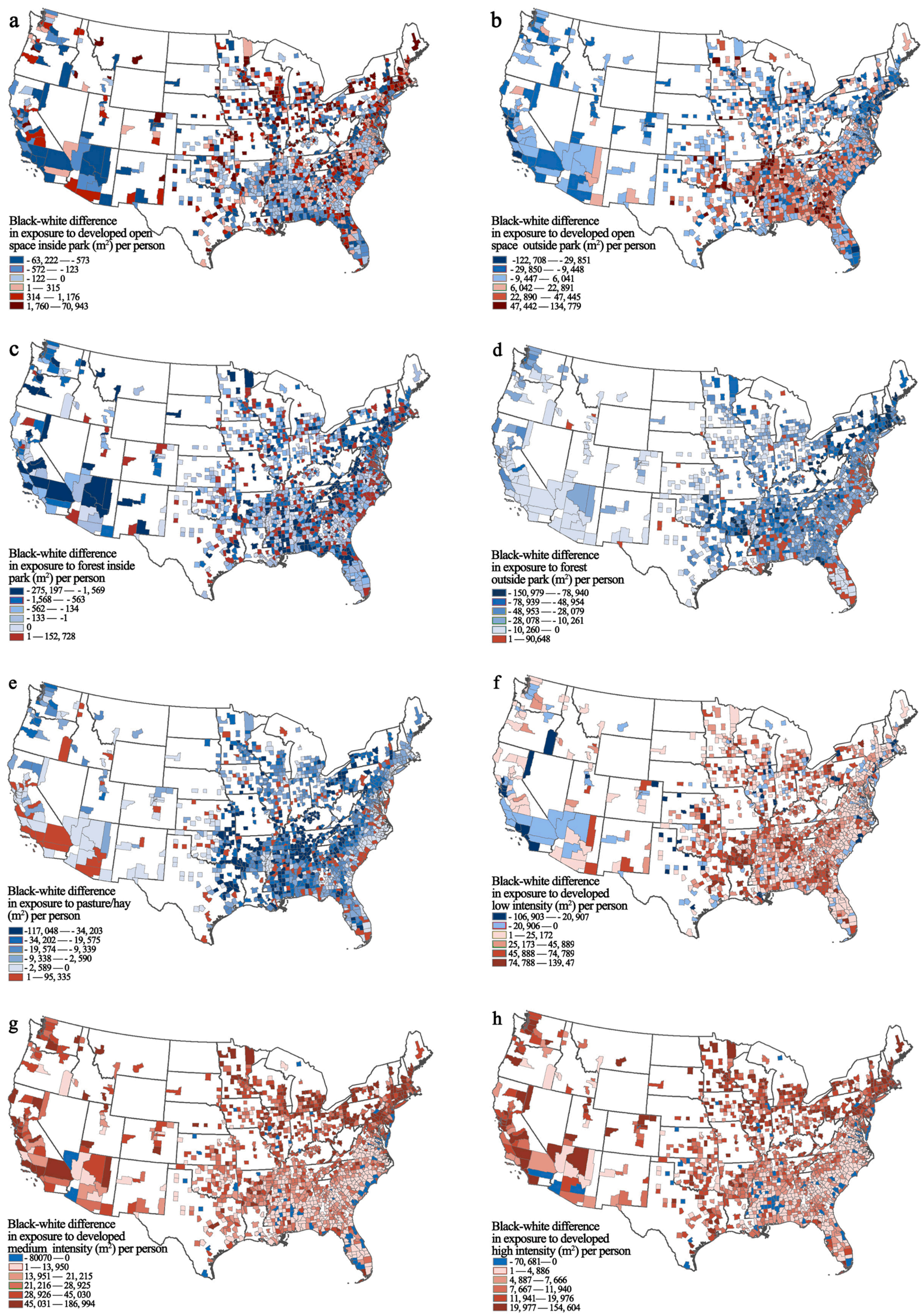

Fig. 7. Within-county racial difference in green and developed space exposure for each of 1416 counties (within the 400 m buffer distance). References to "black" and "white" populations pertain to non-Hispanic black and non-Hispanic white individuals, respectively.

4.1. Unraveling the confluence of race, space, and disease transmission

4.1.1. Green exposure, racial disparity and infection rates

By what mechanisms might equalizing access to green spaces contribute to reducing racial disparities in SARS-CoV-2 infection rates? Drawing from the medical connections established in prior research (e.g., Browning et al., 2021; Chiang & Weng, 2021; Jiang et al., 2016; Kim & Miller, 2019; Klompas et al., 2020; Knobel et al., 2021; Leclerc et al.,

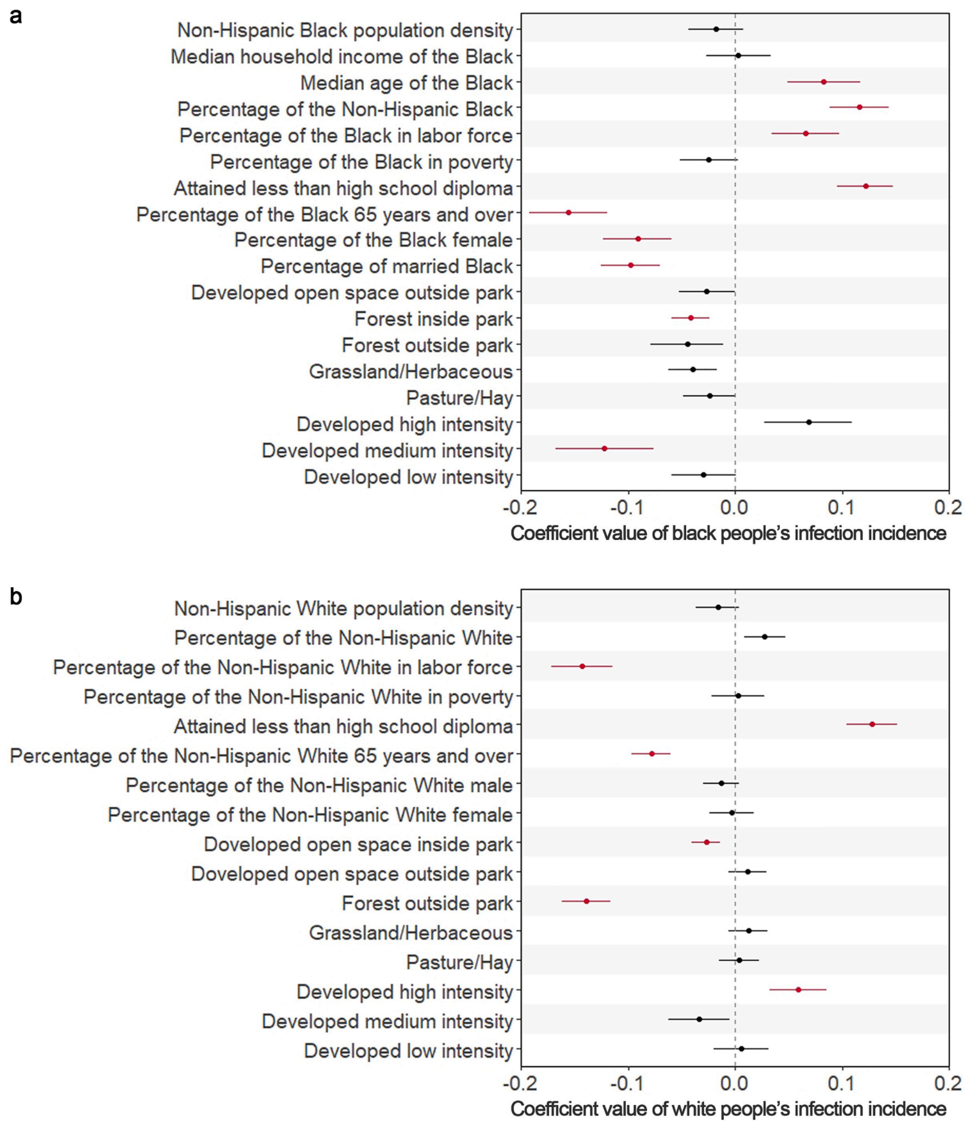

Fig. 8. Associations among green space, developed spaces, and SARS-CoV-2 infection rates. Coefficient values from a negative binomial mixed effects model represent the effect sizes for the relationship between SARS-CoV-2 infection rates for non-Hispanic black (a) and non-Hispanic white (b) individuals, green exposure, developed exposure, and socioeconomic and demographic factors, within a 400 m buffer. Note: coefficient values (dots and bars) represent 95 % CIs. Significant variables are shown in red ($p < 0.05$), and non- significant in black ($p \geq 0.05$).

2020; Lin et al., 2023; Spotswood et al., 2021; Wu et al., 2020a; Wu et al., 2020b; Zhu et al., 2020), we present a conceptual framework (Fig. 11) to elucidate potential mechanisms. First, equitable green space exposure could lead to more uniform air quality exposure across racial lines, potentially influencing infection rates. Elevated levels of airborne pollutants, including PM2.5, PM10, NO2, and O3, are known to heighten SARS-CoV-2 infection rates. Given that COVID-19 is an airborne disease, cleaner air, often found in greener areas, may play a role in equalizing infection rates among different racial groups (Wu et al., 2020a; Klompas et al., 2020).

Second, the link between green spaces and physical activity is well-established (Kim & Miller, 2019; Knobel et al., 2021). Green spaces not only encourage outdoor activities that bolster health against various diseases, including obesity, cardiovascular and respiratory conditions, stroke, and inflammation, but they also enhance immune function (Lu et al., 2021a; Cox et al., 2017; Knobel et al., 2021; Kuo, 2013; Lanki et al., 2017; Christina et al., 2017; Wilker et al., 2014; Bikomeye et al., 2022; da Silveira et al., 2021). These health benefits, in turn, may reduce the rate or severity of SARS-CoV-2 infections within communities (Matsushita et al., 2020; Mohammad et al., 2021; Wu et al., 2020a).

Third, green spaces can be sanctuaries for mental wellness. Prolonged exposure to vegetated spaces has been linked to reduced psychophysiological stress (Browning et al., 2021; Chiang & Weng, 2021; Jiang et al., 2016; Sullivan & Li, 2021), which can translate to a more robust immune system (Kuo, 2015; Segerstrom & Miller, 2004). The interaction between green spaces and enhanced immune responses, attributed to increased Natural Killer cells and other immune boosters, may explain the link between green space exposure and reduced disparities in SARs-CoV-2 infections among black and white residents in the counties we examined.

Lastly, access to green spaces supports outdoor social interactions that inherently reduce SARS-CoV-2 transmission risks. The openness and ventilation of outdoor environments, as opposed to confined indoor spaces, reduce viral transmission possibilities, enabling safer social engagements (Leclerc et al., 2020). Furthermore, being in green spaces and participating in related activities usually occurs outdoors, increasing the likelihood of social distancing and potentially resulting in lower virus concentrations due to the larger physical space and natural air movement (Lin et al., 2023). This is especially crucial for COVID-19, which spreads through the airborne transmission of respiratory viruses (Jiang

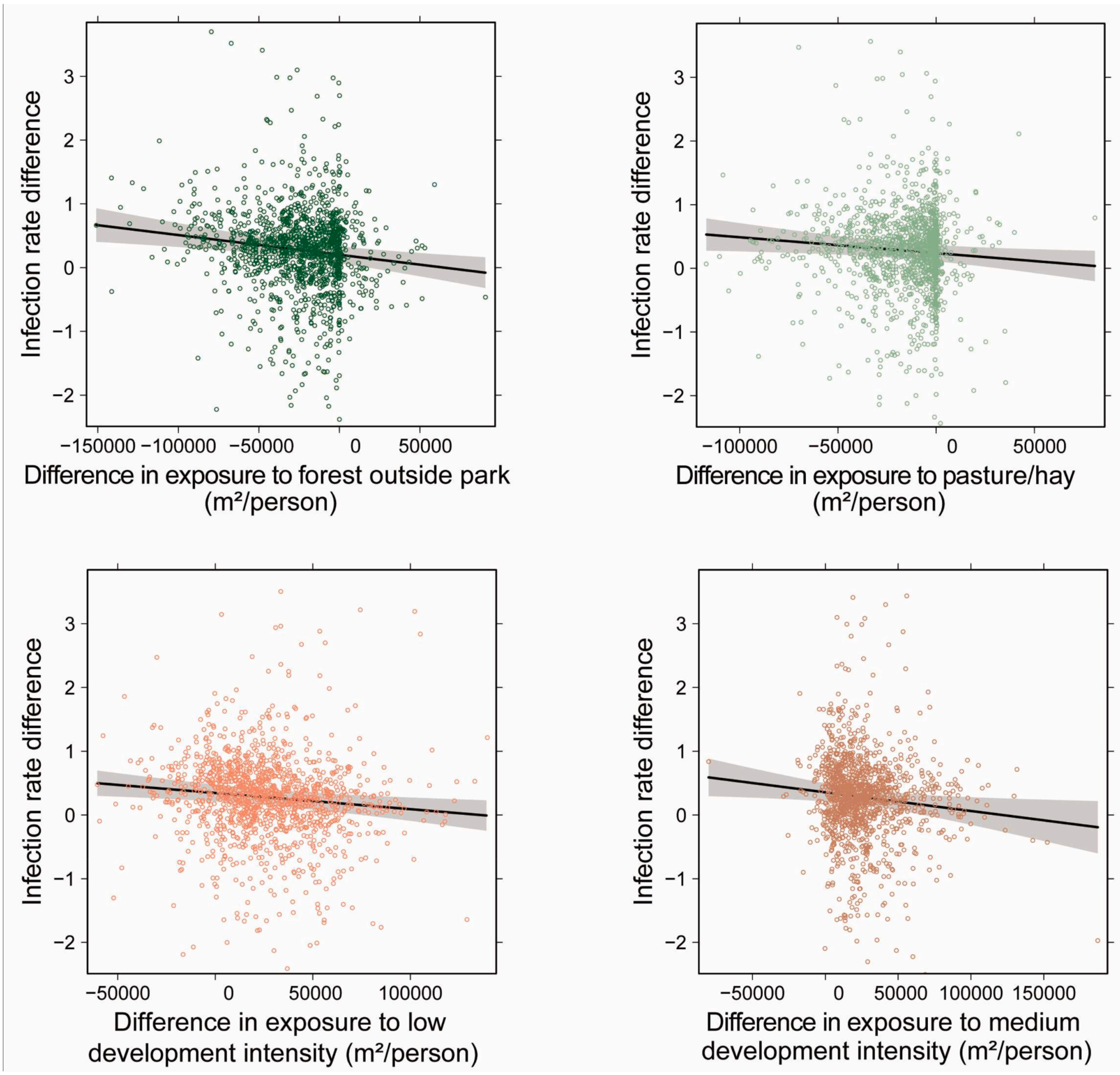

Fig. 9. Green spaces and developed spaces that have significant negative correlation with racial disparity of infection rate. The relative difference of infection rate between non-Hispanic black and non-Hispanic white population was calculated as ln (non-Hispanic black cases/ 100k) - ln (non-Hispanic white cases/ 100k).

et al., 2021; Spotswood et al., 2021).

In the narrative that follows, we weave together the roles of green spaces, racial disparities, and SARS-CoV-2 infection rates, highlighting the delicate equilibrium within urban ecosystems.

4.1.2. Forest exposure's association with racial disparity in infection rates

Our findings indicated that among all landscape types, reduced racial disparities in forest exposure were most potently linked to diminished racial disparities in SARS-CoV-2 infection rates. There are multiple compelling explanations for this observation. First, forest landscapes are the most prevalent type of green landscape in the counties we examined. Forest landscapes encompass what people typically think of as forests (e.g., areas dominated by trees generally greater than 5 m tall and greater than 20 % vegetation cover) and include urban forests which can be comprised of urban parks, street trees, landscaped boulevards, gardens, river and coastal promenades, greenways, nature preserves, wetlands and other green landscapes. The ubiquity of forest landscapes across the US may provide a more even distribution in both urban and rural locales (Yang et al., 2018). This widespread presence may result in more equalized nature exposure opportunities to both black and white populations.

Second, forests promote mental health. Compared to other landscape types, forests have demonstrated superior efficacy in alleviating mental stress and negative emotions (Beil & Hanes, 2013; Jiang et al., 2016). Such benefits may further enhance immune responses, reduce systemic inflammation, and subsequently bolster resistance to infections (Kuo, 2015; Li et al., 2010).

Third, air quality is likely better in near forested landscapes. The intricate, vertically layered foliage profile of forests allows them to capture particulate pollutants than other vegetative forms, such as grasslands and shrubs (Beckett et al., 2000) more proficiently. As a result, forest exposure has been significantly correlated with diminished acute respiratory symptoms (Nowak et al., 2006, 2018) and lower SARS-CoV-2 infection instances (Jiang et al., 2022; Lovasi et al., 2008).

Finally, forests may promote social distancing. Due to their dense canopy, trunk structure, and often winding pathways, forests could inadvertently encourage social distancing (Jiang et al., 2022). Contrarily, while open spaces may have certain advantages in mitigating SARS-CoV-2 infection – such as reducing air pollution and mental stress and encouraging physical activity – these could be negated if they foster

Table 2
Results from the generalized linear mixed effects model.

	VIF	Coefficient estimate	Std. Error	Df	t value	Pr(> |t|)
Intercept		0.28	0.06	38	4.38	<0.001***
General population density	1.89	−0.05	0.02	1301	−1.99	0.047*
Diff. in population density	1.79	−0.05	0.02	1274	−2.22	0.026*
Diff. in median household income	1.60	−0.04	0.02	1297	−1.95	0.052
Diff. in median age	2.69	0.08	0.03	1311	2.76	0.006**
Diff. in percentage of population	1.38	0.21	0.02	1318	8.64	< 0.001***
Diff. in percentage of population in labor force	2.28	0.07	0.03	1294	2.60	0.009**
Diff. in percentage of the population in poverty	1.47	−0.01	0.02	1299	−0.32	0.747
Diff. in attained less than high school diploma	1.34	0.09	0.02	1303	4.13	< 0.001***
Diff. in percentage of the population 65 years and over	2.71	−0.12	0.03	1310	−3.84	< 0.001***
Diff. in percentage of female	2.37	0.01	0.03	1310	0.45	0.650
Diff. in percentage of married population	1.63	−0.04	0.02	1310	−1.73	0.084
Diff. in developed open space inside park	1.36	−0.01	0.02	1281	−0.42	0.676
Diff. in developed open space outside park	1.67	−0.03	0.02	1287	−1.33	0.184
Diff. in Forest inside park	1.36	0.00	0.02	1284	0.18	0.855
Diff. in Forest outside park	1.92	−0.09	0.03	1317	−3.34	<0.001***
Diff. in Grassland/ Herbaceous	1.15	−0.02	0.02	1319	−0.87	0.385
Diff. in Pasture/ Hay	1.62	−0.05	0.02	1311	−2.28	0.023*
Diff. in high development intensity	1.70	0.03	0.03	1308	1.02	0.308
Diff. in medium development intensity	1.94	−0.07	0.03	1316	−2.33	0.020*
Diff. in low development intensity	1.95	−0.07	0.03	1304	−2.78	0.006**

Note: Diff. means difference between non-Hispanic black and non-Hispanic white population. Both green and developed space exposures were measured within the 400 m buffer distance for each race. The general population density is the density of all racial populations.

crowded gatherings. Such detrimental effects may be particularly pronounced in densely populated urban regions (Yang et al., 2022).

4.1.3. Forests outside parks versus inside parks

Several factors may underlie the stronger association between racial disparity in exposure to forests outside parks and SARS-CoV-2 infection rates. Historically, black communities in the U.S. have had distinct interactions with green spaces, often stemming from historical exclusions from parks—particularly larger parks in suburban and rural areas (Byrne & Wolch, 2009; Wolch et al., 2014). Contemporary surveys indicate that black park-goers face challenges, such as feeling unwelcome, limited free time, transportation constraints, and financial burdens associated with distance travel (Iyer et al., 2020; Wolch et al., 2014). While urban parks might be more accessible to black individuals, larger parks in suburban or rural areas remain less accessible. This disparity suggests that forests within parks might exert a less pronounced effect on infection rates than those outside parks (Larson et al., 2021). Contrastingly, forests outside parks are accessible more uniformly across racial lines, potentially leveling the health benefits across communities. Additionally, both racial groups have larger expanses of forests available outside parks than inside, facilitating social distancing and potentially driving reduced infection rates (Jiang et al., 2022).

4.1.4. Urban development intensity, racial disparities, and infection rates

A unique observation from our findings is the pronounced association of racial disparity in low-to-medium urban development intensities with SARS-CoV-2 infection rates, while high-intensity developments showed no such correlation.

What might account for this observation? Residents in high urbanization zones often face amplified virus exposure risks. The close-knit structure of these areas prompts residents to frequently come into proximity with potential carriers, thereby increasing their exposure (Acuto et al., 2020; Teller, 2021; Jamshidi et al., 2020; Kokubun & Yamakawa, 2021). Conversely, the design and expanse of low and medium urban intensity zones can promote outdoor activities, offering a dual advantage: boosting immunity and facilitating physical distancing (Wang et al., 2021). Furthermore, the stress dynamics vary across urban gradients. Residents in high-density urban clusters report higher stress levels, which translates to heightened cortisol levels, impairing the production of lymphocytes, a category of white blood cells instrumental in fending off viruses, including SARS-CoV-2 (Luo & Jiang, 2022; Jiang et al., 2014; Maydych et al., 2017; Ryden et al., 2009).

It is also possible that social capital is influenced by urban development intensity which then impacts infection rates. Areas of high intensity urban development have been associated with lower levels of social capital (Eriksson & Rataj, 2019; Rupasingha et al., 2006), which has shown an inverse relationship with SARS-CoV-2 infection rates and population density (Kokubun & Yamakawa, 2021). In areas of lower density, equitable access to communal spaces may promote community cooperation (Sullivan et al., 2004), which is vital for adhering to pandemic safety measures like mask-wearing and social distancing (Watanabe et al., 2022).

4.2. Implications

The insights from our study carry four implications for landscape and urban planning, each with the potential to reshape public health outcomes across racial lines.

First, the pronounced racial disparities we observed in SARS-CoV-2 infection rates and access to green and developed spaces call for a strategic allocation of public resources. There is a clear need for targeted efforts to enhance natural landscapes in neighborhoods with higher minority populations. This could involve government support for urban greenery initiatives and a reimagining of urban design to create less dense living environments, thereby reducing public health disparities. Specific actions might include investing in urban forestry efforts and

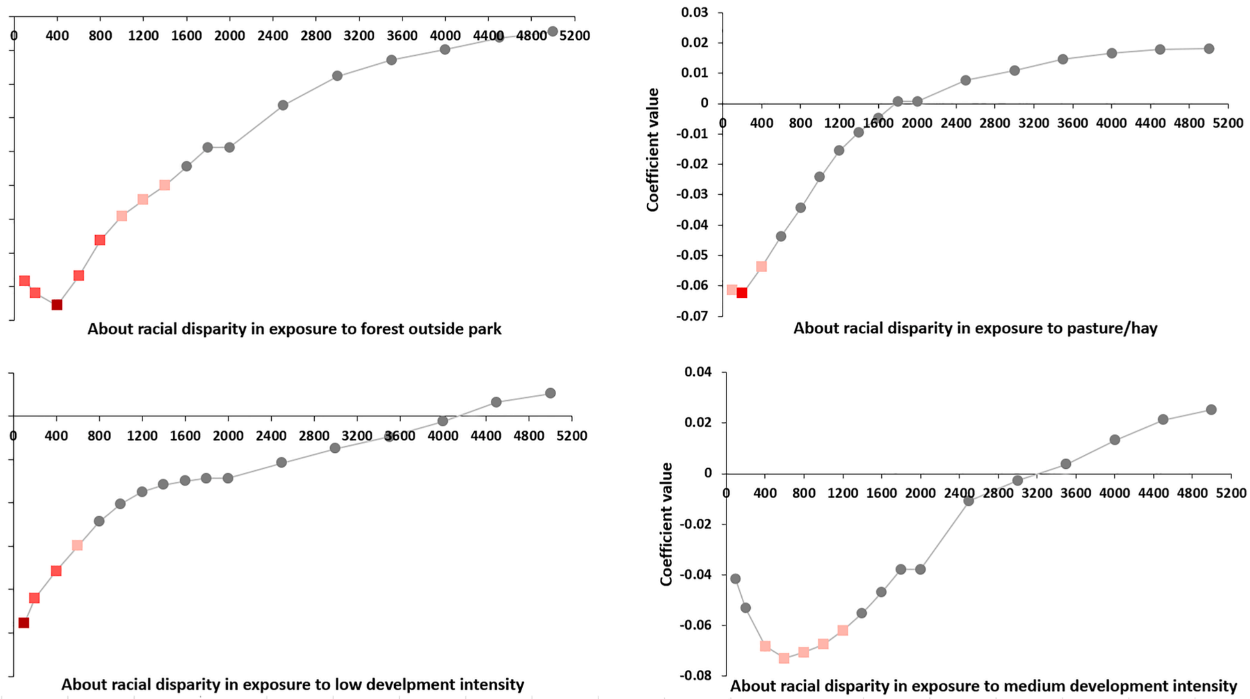

Fig. 10. Coefficient values describing the associations between racial disparity in green and developed space exposure within multiple buffer distances (100m-5 km) and racial disparity in SARS-CoV-2 infection rates. Coefficient values are represented as dots: gray indicates nonsignificant associations, $p \geq 0.5$; Strong to light red indicates significant associations at different levels, $p < 0.001$, $p < 0.01$, and $p < 0.05$ (see detailed results in Table 3).

Table 3
Coefficient values describing the associations between racial disparity in green and developed space exposure within multiple buffer distances (100m-5 km) and racial disparity in SARS-CoV-2 infection rates. Significant levels are at $^{ns}p \geq 0.5$, $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

Buffer distance (meter)	Green space exposure		Developed space exposure	
	Forest outside park	Pasture/ hay	Medium development intensity	Low development intensity
100	−0.078**	−0.062*	−0.042	−0.095***
200	−0.082**	−0.063**	−0.053	−0.084**
400	−0.086***	−0.054*	−0.068*	−0.071**
600	−0.077**	−0.044	−0.073*	−0.060*
800	−0.066**	−0.034	−0.071*	−0.049
1000	−0.059*	−0.024	−0.067*	−0.041
1200	−0.054*	−0.016	−0.062*	−0.035
1400	−0.050*	−0.009	−0.055	−0.032
1600	−0.044	−0.005	−0.047	−0.030
1800	−0.039	0.001	−0.038	−0.029
2000	−0.039	0.001	−0.038	−0.029
2500	−0.026	0.008	−0.011	−0.022
3000	−0.018	0.011	−0.003	−0.015
3500	−0.013	0.015	0.004	−0.010
4000	−0.010	0.017	0.013	−0.002
4500	−0.006	0.018	0.021	0.007
5000	−0.005	0.018	0.025	0.011

prioritizing affordable housing and diverse housing options to alleviate crowded living conditions (Li, 2023; Frumkin, 2021; Jennings & Johnson Gaither, 2015; Rothwell & Massey, 2009). Moreover, promoting mixed-use development can lead to more vibrant, diverse, and less densely populated neighborhoods, contributing to better health outcomes (Bibri et al., 2020).

Second, our findings underscore that not all green spaces and urban developments are equal in their impact on SARS-CoV-2 infection rates and racial disparities. This differentiation suggests that city administrators and public health professionals should be discerning in how they allocate resources, focusing on those landscape settings and development intensities that most effectively reduce infection risks.

Third, the proximity of green spaces and urban areas to residential locations is crucial. The health benefits of forests outside parks, agricultural lands, and urban areas with low to moderate development intensity are most pronounced when these are within a comfortable walking distance (less than 400 m). The protective effects wane with increased distance and become negligible beyond a certain point. This finding suggests that governments should allocate more resources to preserve and develop natural landscapes and areas with low and moderate development intensity within walking distance of residential developments.

Fourth, our research highlights the necessity for interdisciplinary collaboration between urban planners and landscape architects. While previous studies often examine the characteristics of places based on landscape characteristics or levels of urban development, our analysis reveals that both green and developed spaces are significant in mitigating the risk of SARS-CoV-2 infection after accounting for multicollinearity. This suggests that these two elements should be integrated and considered equally vital in urban planning to reduce the risk of airborne infectious diseases.

These implications point towards a more nuanced and targeted approach to urban planning and public health policy, one that recognizes the varied impacts of different types of spaces and the importance of their accessibility to all community members.

4.3. Limitations and opportunities for future research

Our study provides insights into the relationships among racial disparities in environmental exposure and SARS-CoV-2 infection rates, yet it operates within certain constraints that future research can address. One notable limitation is our reliance on aggregated infection data, which may lead to ecological fallacy. To mitigate this possibility, we used high-resolution racial mapping, population-weighted analysis, and within-county comparisons. Despite these efforts, the potential for more precise findings exists, particularly with the use of individual-level data,

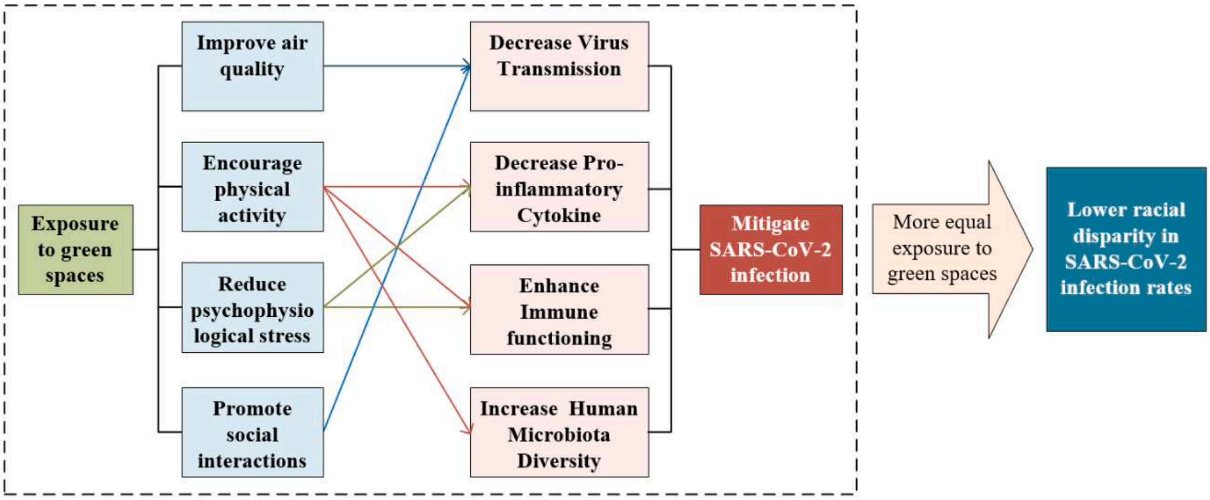

Fig. 11. A pathway framework for potential causal mechanisms linking racial disparities in exposure to green spaces and racial disparities in SARS-CoV-2 infection rates.

which future researchers might explore to strengthen, or perhaps revise, the conclusions drawn above.

The scope of this study was specifically trained on the relationship between racial disparities in environmental exposure and SARS-CoV-2 infection rates, without delving deeply into the racial disparities in socio-economic and demographic covariates. These factors, which include income and education levels, are associated with infection rates and warrant further exploration in public health, urban policy, and landuse planning to fully grasp their impacts.

Although we have identified a correlational relationship in our findings, the question of causality remains. Previous research provides glimpses into a potential causal link, and our proposed theoretical framework supports this notion. Still, future research should seek evidence of causal relationships, possibly through natural experiments, environmental interventions, or longitudinal cohort studies.

Our analysis was primarily confined to black and white populations due to data availability, which limits the generalizability of our findings across the full spectrum of racial and ethnic diversity. This limitation is an invitation for future research to broaden the scope and enrich the understanding of these disparities with more diverse ethnic data.

Finally, the generalizability of our findings across the entire contiguous United States should be approached with caution. In regions with less diverse populations, the applicability of our conclusions may vary. Therefore, future research should aim to encompass a more comprehensive dataset that reflects the diversity of the entire nation.

5. Conclusion

As the immediate crisis of the COVID-19 pandemic wanes, the imperative for deeper understanding and proactive measures becomes clear. This research underscores the critical need for intentional urban and landscape planning that aligns the collective efforts of governments, urban planners, landscape architects, public health professionals, and residents. The aim is clear-cut: to ensure equitable access to diverse, health-promoting landscapes and urban environments, safeguarding racial and ethnic groups against the threat of infection. It is with a hopeful outlook that we propose the findings of this study can inform and shape effective strategies to meet the challenges of future societal and public health challenges.

CRediT authorship contribution statement

Wenyan Xu: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Bin Jiang:** Conceptualization, Data curation, Formal analysis, Investigation, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **William C. Sullivan:** Validation, Writing – review & editing. **Chris Webster:** Writing – review & editing. **Yi Lu:** Conceptualization, Methodology. **Na Chen:** Writing – review & editing. **Zhaowu Yu:** Writing – review & editing. **Bin Chen:** Data curation, Methodology, Supervision, Writing – review & editing.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2023.105135.

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