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Greenspace exposure and COVID-19 mortality in the United States: January–July 2020

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ABSTRACT

Background: Mortality from the novel coronavirus disease-2019 (COVID-19) continues to rise across the United States. Evidence is emerging that environmental factors may contribute to susceptibility to disease and mortality. Greenspace exposure promotes enhanced immunity and may protect against risk of mortality among those with COVID-19.
Objectives: Our objective was to determine if high county level greenspace exposure is associated with reduced risk of COVID-19 mortality.
Methods: Greenspace exposure was characterized in 3049 counties across the conterminous United States using Leaf Area Index (LAI) deciles that were derived from satellite imagery via Moderate Resolution Imaging Spectroradiometer from 2011 to 2015. COVID-19 mortality data were obtained from the Center for Systems Science and Engineering at Johns Hopkins University. We used a generalized linear mixed model to evaluate the association between county level LAI and COVID-19 mortality rate in analyses adjusted for 2015–2019 county level average total county population, older population, race, overcrowding in home, Medicaid, education, and physical inactivity.
Results: A dose-response association was found between greenness and reduced risk of COVID-19 mortality. COVID-19 mortality was negatively associated with LAI deciles 8 [MRR = 0.82 (95% CI: 0.72, 0.93)], 9 [MRR = 0.78 (95% CI: 0.68, 0.89)], and 10 [MRR = 0.59 (95% CI: 0.50, 0.69)]. Aside from LAI decile 5, no associations were found between the remaining LAI deciles and COVID-19 mortality. Increasing prevalence of counties with older age residents, low education attainment, Native Americans, Black Americans, and housing overcrowding were significantly associated with increased risk of COVID-19 mortality, whereas Medicaid prevalence was associated with a reduced risk.
Discussion: Counties with a higher amount of greenspace may be at a reduced risk of experiencing mortality due to COVID-19.

1. Introduction

The outbreak of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has spread rapidly across the world since December 2019. SARS-CoV-2 is highly pathogenic, transmissible, and has high morbidity and mortality among those that develop the novel coronavirus disease 2019 (COVID-19). On January 30, 2020, the World Health Organization (WHO) Director General declared the COVID-19 outbreak as a Public Health Emergency of International Concern (World Health Organization, 2020). In 2020, there were estimated to be about 352,700 deaths in the United States due to COVID-19 (Johns Hopkins and Medicine, 2020), reaching the third leading cause of death for persons aged 45 through 84 years and the second leading cause of death for those aged 85 years or older (Woolf et al., 2021).

Previous work has shown that patients in central China with a severe-type of COVID-19, classified as having respiratory distress, oxygen

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saturation ≤93%, and arterial blood oxygen partial pressure/oxygen concentration ≤200 mm Hg, compared to patients without symptoms, were more likely to: (1) be older in age; (2) have chronic conditions (hypertension, cardiovascular disease); (3) have symptoms of shortness of breath and fatigue; and, (4) have unhealthier levels of inflammatory cytokines, infection-related biomarkers (e.g., C-reactive protein), immunoglobin M, lymphocytes (e.g., neutrophil-lymphocyte ratio (NLR)), leukocytes, and T cells (Qin et al., 2020). These clinical characteristics indicate a dysregulated immune system that may cause people with an already weaker immune system (e.g., older adults with chronic conditions) to be more susceptible to severe cases of COVID-19 that further impairs their immune system (Qin et al., 2020).

Evidence is emerging that environmental factors, such as air pollution, exacerbate symptoms among COVID-19 patients (Copat et al., 2020). Air pollution is a major environmental cause for disease and premature death and may worsen COVID-19 severity by negatively impacting the human immune system (Copat et al., 2020; Gakidou et al., 2017). In contrast, greenspace exposure may reduce risk of COVID-19 mortality through multiple underlying mechanisms that include reduced air pollution and microbial diversity exposure. Early and long-term exposure to greenspace may influence mortality due to COVID-19 through the improved immune regulation pathway, as greenspace, particularly the natural environment, serves as a setting that provides exposure to microbial diversity, such as through soil, plants, and wildlife (Frumkin et al., 2017; Rook, 2013; Taylor and Hochuli, 2017). Socio-economic status among individuals and neighborhoods is an important predictor of the presence and utility of residential greenspace exposure and risk of morbidity and mortality outcomes. Studies have evidenced low levels of greenspace among low-income neighborhoods which may be due to individuals with higher socio-economic status choosing to move to greener neighborhoods (Brown et al., 2018; Engemann et al., 2019). Individuals with low socio-economic status compared to those with higher socio-economic status tend to experience larger reductions in risk of diseases (e.g., Alzheimer's Disease, circulatory disease) when exposed to increasing levels of greenspace (Brown et al., 2018; James et al., 2015).

To our knowledge, there has been no study to assess the association of greenspace exposure and COVID-19 mortality. We analyzed county level data comparing counties organized by greenness deciles to assess whether COVID-19 deaths were higher in counties with lower greenspace deciles.

2. Methods

All county level data used in the analysis were obtained from publicly available sources. Detailed information for the outcome variable, exposure variable and all covariates is provided in Table 1, including links to access the raw data.

2.1. COVID-19 mortality data

We obtained COVID-19 death counts at the county level from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). JHU CSSE collects comprehensive county level COVID-19 data reported by several data sources (e.g., Centers for Disease Control and Prevention, World Health Organization) in real-time and provides the data as a repository for public access through the GitHub platform (Dong et al., 2020). JHU CSSE did not have COVID-19 data for 57 counties. Fig. 2 showcases which counties are missing from analysis in the second map with a large number missing in Utah. In addition, at the time of this study, this data source had collapsed death counts into one data point ("New York City") across the Kings, Queens, Richmond, Bronx, and New York boroughs. Due to the extremely influential effect of the "New York City" data point on our model, it was removed from final analysis. In addition, we omitted the Ogata Lakota county due to this county having no listed adjacent counties in the United States Census Bureau county adjacency dataset described later in this paper, which was used to assess spatial autocorrelation in the model residuals using Moran's I test statistic.

Cumulative counts of COVID-19 deaths were obtained from January 21, 2020 to July 29, 2020. Fig. 1 displays a violin plot of the kernel probability density of COVID-19 deaths across Leaf Area Index (LAI) deciles, where LAI decile corresponds to 0–10%, 10–20%, and so on. Each violin represents one LAI decile group that includes a boxplot to indicate median value and interquartile range of log COVID-19 deaths at the county level with dots representing outliers.

2.2. Greenspace exposure

Our exposure metric of primary interest was Leaf Area Index (LAI). LAI is defined as the leaf surface area per unit ground surface area. LAI has been often used in hydrologic or plant growth models and, more recently, in epidemiological studies providing evidence that greenspace exposure is associated with improved health outcomes (Engemann et al.,

Table 1
Outcome, explanatory and covariates used in study analysis with definitions, descriptions and source information.

Domain	Variable	Survey Description	Transformation	Source
Outcome variable:	COVID-19 deaths	County level COVID-19 death counts from 1/21/20 to 7/29/20	None	Johns Hopkins University the Center for Systems Science and Engineering (JHU-CSSE) Coronavirus Resource Center (https://coronavirus.jhu.edu/); URL: https://github.com/CSSEGISandData/COVID-19.
Explanatory variable:	Leaf Area Index (LAI)	LAI across the conterminous U.S (CONUS) at 250-m resolution	Equal deciles of county level LAI	201-2015 MODIS, NDVI LAI. URL: https://topofire.dbs.umt.edu/public_data/helmsdeep1/health_projects/MODIS_data
Education	Less than a HS diploma or equivalent	Educational attainment for the population 25 years and over	Percent	US Census. 2015–2019 American Community Survey 5-year estimates. URL: https://www.census.gov/programs-surveys/acs/data.html
Overcrowding	Homes (rented and owned) with a 1.01 plus ratio of occupants per room	Tenure by occupants per room	Percent	
Socio-Economic Status	Adults ages 18–64 with Medicaid	Health insurance type by age	Percent	
Population	Total Population	Total population counts	Log-transformed	
Older age	65 years and older	Counts of individuals over 64 years old	Percent	
Race	Native American; Black	Percent of people who identify as Black or Native American.	Percent	
Health behavior	Physical inactivity	Percent of adults ages 20 and over reporting no leisure-time physical activity.	None	2016 United States Diabetes Surveillance System. URL: https://www.countyhealthrankings.org/explore-health-rankings/rankings-data-documentation

2019; Orioli et al., 2019). We developed 250 m resolution annual maximum LAI maps for the conterminous United States (CONUS) using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) using the MOD13Q1 product 16-day vegetation indices. Each 16 day normalized difference vegetation index (NDVI) image was converted to LAI following methods described by Gitelson (2004). We then extracted the mean 2011–2015 LAI average for each of the 3049 United States counties. Following Engemann et al. (2019), we created equal deciles of LAI exposure at the county level to test for a dose-response association with COVID-19 mortality. For background, NDVI is an indicator using land surface reflectance of visible and near-infrared light reflected by vegetation that is displayed in a multispectral raster dataset. LAI is a transformation of NDVI that represents the number of layers of vegetation coverage and is highly correlated to NDVI, but is more of a structural climate variable to aid in quantifying greenness (Fang et al., 2019).

2.3. Predictors of Covid-19 mortality

We considered a number of predictors of COVID-19 mortality as potential covariates in analyses. A number of studies have found clinical, demographic, and environmental risk factors linked to COVID-19 mortality. Such clinical, demographic, and environmental risk factors include having chronic diseases, such as hypertension, diabetes, or coronary heart disease; being immunocompromised or having abnormal immunity; older age; male sex; disability; Black or Native American race; poverty; public insurance (e.g., Medicaid); obesity; days since first case reported in a county; air quality (e.g., PM2.5); hospital beds; overcrowding in home; and, education attainment (Abedi et al., 2020; Brandt et al., 2020; Millett et al., 2020; Price-Haywood et al., 2020; Tian et al., 2020; Wu et al., 2020; Zhao et al., 2020). Of these variables, the following were publicly available at the county level (see details in Table 1): percent with low education attainment, percent of overcrowding in home, percent on Medicaid as a proxy measure for low socio-economic status, total population size, percent who are Native American and Black American races, percent ages 65 and over, and percent of physical inactivity as a proxy measure for chronic morbidity (e.g., heart disease, type II diabetes, various cancers) (Bull et al., 2004).

2.4. Statistical analysis

We used negative binomial regression using the generalized linear mixed model (GLMM) 'glmmTMB' package (Brooks et al., 2017) in R version 4.0.2 (R Core Team, 2019) to evaluate the association between LAI decile and COVID-19 mortality. State was included in analyses as a random effect to account for variation in state mandates and recommendations to suppress the spread of COVID-19, which also partially accounts for spatial autocorrelation. Analyses were adjusted for education (No high school diploma or equivalent) prevalence, overcrowding (homes with a ratio of 1.01 or more per room) prevalence, Medicaid (18–64 years old) prevalence, older age (adults 65+) prevalence, Black and Native American race prevalence, physical inactivity prevalence, total county population, and average COVID-19 mortality among neighboring counties. This last covariate was added to the model as a predictor variable to account for spatial autocorrelation that was originally present in our model, resulting in uncorrelated residuals. We applied restricted maximum likelihood (REML) with a negative binomial link function, included state as a random effect, and applied a single zero-inflation parameter that, collectively, account for: (1) the number of parameters (fixed effects) by producing unbiased estimates of the variance components; (2) the presence of excess zeros; (3) over-dispersion; and (4) state-level variability in our data. It is important to address all of these model features within the GLMM when working with clustered data (Takele et al., 2019). The GLMM used county population as an offset thus modeling COVID-19 rates on a log scale. Exponentiating results allows back-transformation of study findings to the original metric.

To assess collinearity among predictors within our full model, we calculated variance inflation factors (VIF). VIF values of 5 or greater indicate a potential collinearity problem (Hair et al., 2011). For our mode, all factors were less than 2.5 indicating no serious multicollinearity. All analyses were performed using R 4.0.2. Mortality rate ratios (MRR) with 95% confidence intervals (CI) were used to compare LAI deciles. MRRs are exponentiated parameters from the GLMM used to summarize main analysis findings and can be interpreted as the relative difference in the COVID-19 mortality rate associated with increasing LAI deciles compared to LAI decile 1 (counties with 0–10% LAI coverage).

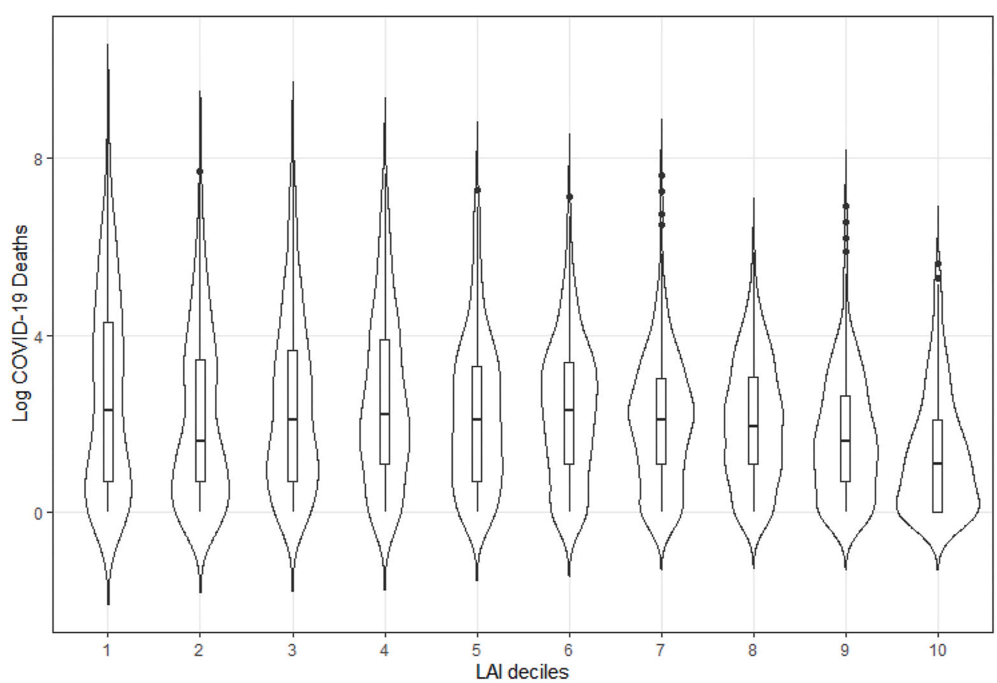


Fig. 1. Violin plots of COVID-19 death counts by LAI decile among 3049 counties.

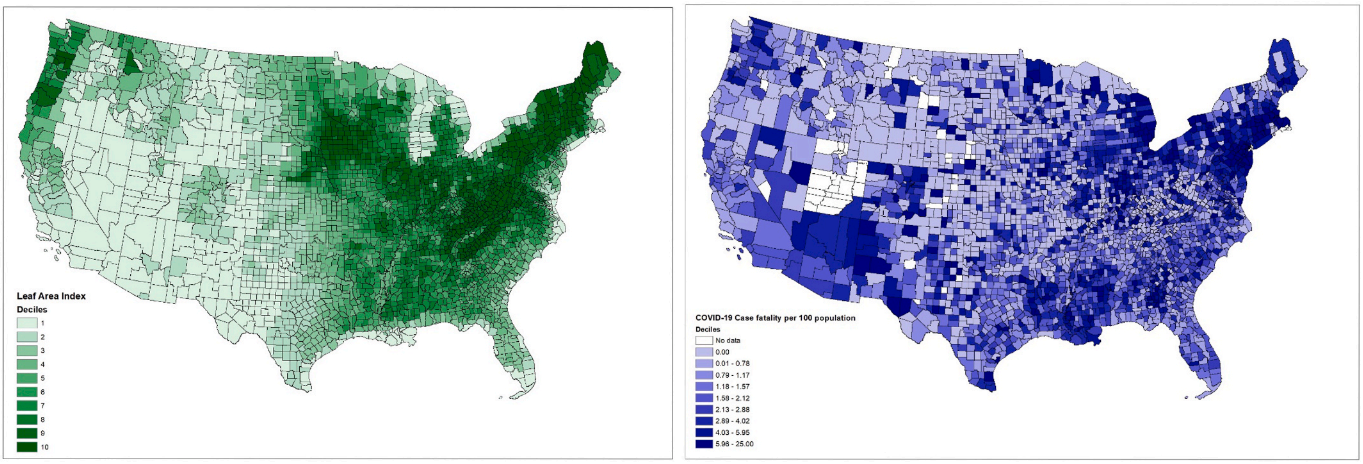


Fig. 2. Side-by-side maps of Leaf Area Index (LAI) deciles and COVID-19 case fatality per 100 population by deciles for conterminous counties, U.S.A.

2.5. Spatial autocorrelation

We used Moran's I test statistic to assess spatial autocorrelation of COVID-19 mortality residuals. Similar to a spatial epidemic study on the COVID-19 outbreak, we defined neighbors as counties that share a border (Kang et al., 2020) and obtained lists of adjacent counties from the United States Census Bureau (https://www.census.gov/programs-surveys/geography/library/reference/county-adjacency-file.html). Values near 0 for Moran's I statistic indicate a lack of spatial autocorrelation; positive values indicate clustering of similar values and negative values indicate clustering of dissimilar values. Using a boundary-based neighborhood definition, a permutation test indicated insufficient evidence of spatial autocorrelation in the model residuals (I = 0.0098; p = 0.16). By incorporating the mean COVID-19 mortality of a county's neighbors as a predictor variable and including state as a random effect in the model (see Table 1 for details), we were able to adequately account for spatial autocorrelation and implement a zero-inflated, negative binomial mixed model for COVID-19 mortality.

2.6. Sensitivity analysis

Rural/urban differences are not directly accounted for in our study due to a concern of high collinearity with the existing total county population variable that is used to calculate the COVID-19 response rate. In addition, we observed that urban settings have less greenness than rural settings in our study, and mortality due to COVID-19 may vary by rural/urban status. As a result, rurality may confound associations between greenspace and COVID-19 mortality. To identify confounding by rural counties, we conducted a sensitivity analysis similar to a separate study assessing air pollution on COVID-19 mortality to determine if counties with a small number of cases were overly influential (Wu et al., 2020). Specifically, we excluded counties with 10 or fewer confirmed COVID-19 cases to assess the robustness of our results (Wu et al., 2020).

3. Results

3.1. Overview

The study utilized findings from 3049 counties across the CONUS. Of the 3049 counties included in final analysis, 851 (27.9%) had zero reported deaths and 247 (8.1%) had 10 or fewer confirmed cases of COVID-19 as of July 29, 2020. Table 2 provides characteristics of counties by LAI decile that were used in the final analysis. Total population counts, prevalence of Medicaid coverage, overcrowding in home, and race differed by decile.

Fig. 2 displays two maps of the spatial variation of LAI deciles across the CONUS and COVID-19 case fatality per 100 population. LAI density is more prominent in the eastern part of the country and west of the Rocky Mountain divide, where county populations tend to be larger.

3.2. Main analysis using LAI deciles

A significant association was found between increasing LAI deciles and reduced COVID-19 mortality rate. Fig. 3 displays the unadjusted and adjusted Mortality Risk Ratios (MRR) for LAI deciles. The unadjusted MRR values make no adjustments for the effects of the model predictors. The adjusted MRR values use the negative binomial model coefficients to adjust these ratios based on the model predictions. In comparison to the lowest LAI decile 1 (0–10% greenness), counties within LAI deciles 8–10 have respectively, a 18% [MRR = 0.82 (95% CI: 0.72, 0.93)], 22% [MRR = 0.78 (95% CI: 0.68, 0.89)], and 43% [MRR = 0.59 (95% CI: 0.50, 0.69)] reduced risk for COVID-19 mortality. No corrections were made for multiple comparisons.

3.3. Significant covariates

Counties with an increasing prevalence of Medicaid coverage among populations ages 18–64 years old were found to have a significant reduced risk of COVID-19 mortality (4% increase in MRR) [MRR = 0.98 (95% CI: 0.97, 0.99)]. We speculate a possible explanation for this is that workers who have lost their jobs during the COVID-19 pandemic likely had differential access to Medicaid in states that opted in for Medicaid expansion. For instance, while COVID-19 testing has been largely covered by the government, treatment for the COVID-19 has not (Woolhandler and Himmelstein, 2020).

Counties with an increasing prevalence of Native Americans (2% increase in MRR) [MRR = 1.02 (95% CI: 1.02, 1.03)], Black Americans (2%) [MRR = 1.02 (95% CI: 1.02, 1.02)], low education attainment (5%) [MRR = 1.05 (95% CI: 1.04, 1.06)], overcrowding (5%) [MRR = 1.05 (95% CI: 1.03, 1.08)], and aged 65 and over (4%) [MRR = 1.04 (95% CI: 1.03, 1.04)] were found to have significant increased risk of COVID-19 mortality.

3.4. Sensitivity analysis for unmeasured confounding findings

Our study findings remained significant for LAI deciles 8–10 when conducting the sensitivity analysis. MRR values of COVID-19 mortality for LAI deciles among only counties with greater than 10 confirmed COVID-19 cases produced nearly identical results to those displayed in Fig. 3. Thus, the analysis was insensitive to measures of COVID-19 mortality in counties with small numbers of cases.

Table 2
Selected characteristics of 3049 counties by LAI decile.

Variables	Greenspace (Leaf Area Index) by decile									
	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile10
Total population: *n*	10,081,570	413,035	2,606,868	4,646,630	1,290,360	1,221,744	1,043,530	2,195,502	798,808	824,772
Over 64 [% (SD)]	18.7 (6.0)	20.5 (3.4)	19.0 (5.9)	19.0 (6.0)	18.9 (5.2)	18.4 (4.5)	17.8 (3.6)	18.1 (3.3)	18.7 (2.8)	19.2 (3.0)
No high school diploma or equivalent [% (SD)]	15.1 (8.7)	13.6 (6.3)	13.7 (7.5)	11.5 (5.6)	12.1 (5.4)	13.8 (6.0)	13.2 (5.2)	13.7 (5.7)	12.8 (5.3)	12.1 (5.2)
Medicaid [% (SD)]	11.4 (8.2)	15.3 (8.6)	9.0 (7.1)	8.4 (5.7)	9.6 (5.7)	10.1 (5.2)	10.1 (5.0)	11.6 (5.6)	11.5 (5.1)	12.0 (5.5)
Overcrowding [% (SD)]	3.4 (2.7)	1.6 (1.0)	3.2 (2.6)	2.8 (2.1)	2.2 (1.5)	2.3 (1.3)	2.1 (1.2)	2.0 (1.1)	1.8 (1.0)	1.6 (1.0)
Black [% (SD)]	5.6 (9.8)	2.1 (2.7)	4.0 (7.9)	6.6 (9.5)	14.4 (17.9)	17.1 (18.8)	15.2 (17.8)	14.5 (18.8)	9.5 (15.2)	3.7 (6.6)
Native American [% (SD)]	2.9 (8.5)	0.8 (5.2)	3.3 (10.6)	3.3 (10.5)	2.8 (7.3)	1.3 (3.8)	0.6 (2.3)	0.7 (2.6)	0.6 (1.6)	0.6 (3.5)
Physical inactivity [% (SD)]	24.9 (5.1)	25.9 (5.1)	26 (5.8)	28.4 (5.8)	28.8 (5.9)	28 (6.0)	29 (6.1)	28.5 (5.6)	27.6 (4.5)	27.8 (5.2)

Note: Data presented as percentages (%) are the combined estimated prevalence at the county level. LAI decile ranges, such as Decile 1 corresponds to decile 0–10%.

4. Discussion

We found a reduced COVID-19 mortality rate with high greenspace values. Specifically, a dose-response association was present between LAI exposure, particularly between the top 3 greenspace deciles, and reduced risk of COVID-19 mortality. Our study findings add to the literature of the potential protective effect of greenspace exposure via Leaf Area Index, on the risk of COVID-19 mortality. This is the first ecological study to assess the association between greenspace exposure and mortality prevalence of those contracting the novel Coronavirus disease 2019.

Other studies have found associations between greenspace exposure and positive health impacts citing various underlying mechanisms. Low-income neighborhoods and populations with low socio-economic status have experienced lower presence of or lower access to greenspace exposure compared to higher income neighborhoods; however, individuals with a low socio-economic status background tend to utilize greenspace more and demonstrate greater benefits in reduced risk of diseases compared to their higher-income counterparts (James et al., 2015; Brown et al., 2018; Jarvis et al., 2020). Such findings demonstrate the substantial positive impact greenspace has for low-income neighborhoods and among individuals with low socio-economic status.

In a series by Rook et al. (2017), authors assert that early and continued exposure to the natural environment evidences a protective effect against inflammation-associated diseases brought about by the increasing exposure to novel pathogens that are transmitted by means of crowding due to a growing population (Rook et al., 2017). Specifically, authors note the underlying mechanism is exposure to immunoregulation-inducing macro- and microorganisms found in soil, plants and wildlife that are all housed in natural environments (Rook et al., 2017). Of primary interest is the recent assertion that clinical adverse outcomes from COVID-19 are linked to immunity by means of having a diverse gut microbiota, which is influenced by a combination of early exposure to environmental factors, genetics, and diet (Dhar and Mohanty, 2020).

Several underlying mechanisms of greenspace exposure that positively impact human health are discussed in depth by Frumkin et al. (2017), which include psychological benefits, social contact, physical activity, and improved air quality (Frumkin et al., 2017). We speculate that immunoregulation and reduced air pollution are likely underlying mechanisms that explain the observed association between higher levels of greenspace exposure and reduced risk of COVID-19 mortality. We assume that the shared underlying mechanisms being the immune system and air pollution, are differentially impacted by our study exposure and outcome. As mentioned previously, COVID-19 severity has been linked to air pollution and weaker immune systems, which may cause high-risk individuals to experience worse conditions from the virus inducing a cytokine storm and further damaging tissue (Qin et al., 2020; Wu et al., 2020). In contrast, greenspace exposure has been linked to reduced air pollution and improved immune functioning capacity (Dadvand et al., 2012; Marselle et al., 2019; Paciência et al., 2020).

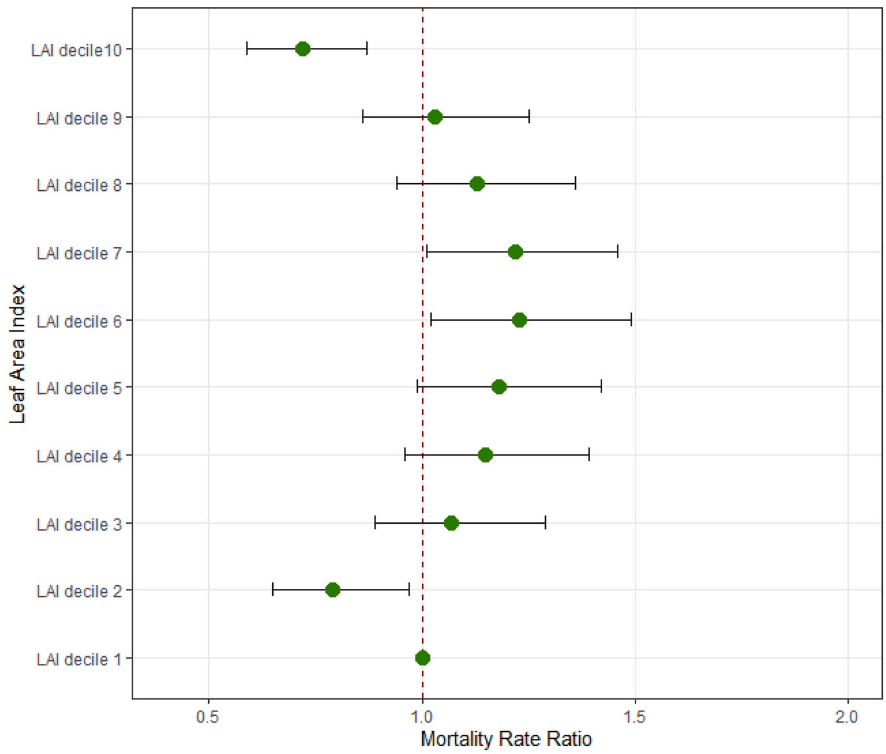
4.1. Strengths and limitations

Strengths of our study include the inclusion of leaf area index (LAI) as an indicator of greenspace exposure. LAI also provides quantification of greenspace by measuring layers of plant growth increasing the sensitivity of correctly identifying natural environments, such as forested areas, that often are home to wildlife and other immunoregulation-enhancing benefits. In addition, we had sufficient variability at the county level to detect differences in greenness and COVID-19 mortality outcomes. Our study findings may be relevant to other countries with similar socio-economic status and physical features. Our approach may be used to incorporate random effects, such as state-level policies around COVID-19 testing and mandate efforts (e.g., requiring mask in public settings) in future studies.

Our study had several limitations. Unmeasured confounding is of primary concern in that we rely mainly on ecological measures at the county level that do not account for potential individual-level confounding factors and do not account for regional variations of outbreaks. There are several potential factors that are relevant to risk of COVID-19 mortality that were not addressed in our study. For example, we did not directly measure comorbidities, such as hypertension, coronary heart disease, or diabetes, or air pollution status. Failure to include the five boroughs in New York that comprise "New York City" due to having too great of an effect on the model was a limitation in that these boroughs were once the epicenter of the COVID-19 outbreak and had a low LAI decile during the study period. In addition, there have been significant land coverage changes over time that may hinder the representation of greenspace exposure. For instance, one study found that approximately 4% of forests were lost from 2001 to 2016 in the conterminous United States (Homer et al., 2020). Lastly, although physical inactivity is a proxy measure for select chronic conditions that have been found to be risk-factors for the study outcome, the absence of direct measures further limits our study findings.

5. Conclusion

Our study findings indicate a dose-response association between greenspace and reduced risk of COVID-19 mortality as seen in Fig. 3. Climate change may influence infectious disease outbreaks and subsequent disease-related mortality and morbidity as we continue to experience pollution and diminishing greenspaces (Marselle et al., 2019). Future studies might update the current study when more up-to-date measures become available, such as the 2020 U.S. Census data. It would also be worthwhile to control for important COVID-19 mortality a



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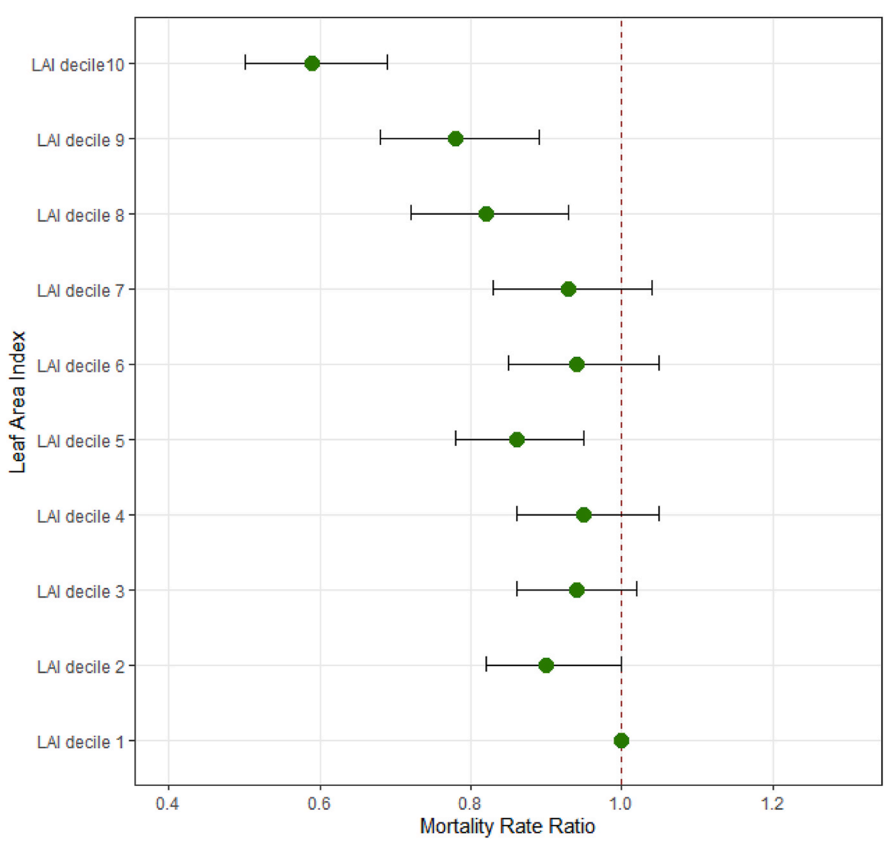

Fig. 3. Unadjusted and adjusted COVID-19 Mortality Rate Ratio by LAI deciles. The unadjusted MRR values make no adjustment for the effects of model predictors. The adjusted MRR values use the negative binomial regression coefficients (95% CI) of COVID-19 death rates and exposure to greenspace (Leaf Area Index) by decile, adjusted for education, overcrowding, Medicaid (ages 18–64), age 65 and over, race (Black and Native American), physical inactivity, and neighbor COVID-19 mortality average. No corrections were made for multiple comparisons.

risk-factors discussed earlier that can be measured at the individual level. The public health impact from our study findings point to the need to preserve our natural environments and partner with various fields to increase greenspace in cities to protect human health.

Data sharing

Data and code used in this study are provided www.github.com/computationalecologylab/LAI_COVID/.

Credit author statement

Helen Russette: Conceptualization, Methodology, Formal analysis, Data curation, Writing – review & editing; Jon Graham: Methodology, Formal analysis, Data curation, Writing – review & editing, Supervision; Zachary Holden: Methodology, Writing – review & editing; Erin O. Semmens: Writing – review & editing, Funding acquisition; Elizabeth Williams: Writing – review & editing; Erin L. Landguth: Methodology, Formal analysis, Writing – review & editing, Supervision.

Declaration of competing interest

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

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